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混合格位傳遞模式之
基因模糊邏輯號誌控制

Genetic Fuzzy Logic Signal Control with Mixed-Traffic Cell Transmission Modeling

指導教授：邱裕鈞

研 究 生：黃彥斐

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Genetic Fuzzy Logic Signal Control with Mixed-Traffic Cell Transmission Modeling

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混合格位傳遞模式之基因模糊邏輯號誌控制

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摘要

在現今台灣都會地區內，隨著工商業活動的頻繁、所得的提高促使汽機車持有率不斷的遽升，然而在原有的都市道路幾何設計之下，道路難以再增加其道路容量，故此現象所造成的車輛擁擠、停等延滯等，將使得駕駛人所花費的時間成本難以估計，除此之外，油耗、噪音…等環境污染問題更日益嚴重。因此，交通管理策略之一的交通號誌控制，在此狀況下就顯的非常重要。一個有效率的交通號誌控制系統，不僅可以解決因道路容量不足而形成的壅塞，更可以減少油料的浪費、二氧化碳氣體的排放，甚至提升道路交通安全。

交通號誌控制理論面上大致可分為離線（off-line）控制與線上（on-line）控制，離線控制主要是事先經由調查員調查各時段之車流資料特性，然後經由號誌時制軟體運算求得適當之號誌時制並放入控制器內加以執行運作。惟此控制方式難以因應瞬息萬變之車流量變動並即時更改時制計畫，其中定時號誌控制（pretimed signal control）就屬此類；至於線上控制方式也就是考慮動態的觀念，利用偵測器（detector）即時的自動傳回各種車流資料，再經由軟體運算後得到一新時制計畫，然後迅速回傳予路口控制器加以執行，因此可以即時反映交通車流狀況。

觸動式號誌控制、動態號誌控制以及適應性號誌控制均屬於線上控制的範疇，其中，適應性號誌控制由於具有彈性、適用性及最佳化等特性，因此，在近年來被廣泛使用。一些較著名的適應性號誌控制如 SCATS、SCOOT 及 OPAC 等，然上述模式均以數學式來研定其控制變數之門檻值，並據以作為控制邏輯之核心，但由於交通狀況充滿著不確定性，倘若以明確值來訂定門檻，恐怕會造成控制績效的不彰。基此，近年來有一些研究透過模糊邏輯控制器(fuzzy logic controller, FLC)來改善此問題。透過偵測器所收集之交通資料，可以應用 FLC 來決定號誌時相及時制計畫。然在 FLC 控制系統中，雖然推論引擎及解模糊化方法都有一貫的理論依據可遵循，但對於邏輯規則及隸屬函數必須由訪談專家加以主觀設定，導致其應用性大受影響。故近年來漸有相關研究利用人工智慧方法，例如基因演算法（Genetic algorithms, GAs）之樣本學習方法建構 FLC，以克服主觀設定偏頗之問題。然而，透過基因演算法同時或連續學習邏輯規則及調整隸屬需要耗費相當多的時間以及產生部分不合理的學習結果。

為了避免上述的缺點，本研究根據反覆 GFLC (Chiou and Lan, 2005)，提出一逐步迴歸的模糊邏輯控制器(Stepwise Genetic Fuzzy Logic Controller, SGFLC)，來學習邏輯規則

及調整隸屬函數。逐步演算法選擇邏輯規則及隸屬函數之概念與逐步迴歸相似，在既有規則庫中，一次僅選擇一個能使適合度值改善最大的規則，直到入選的規則均無法改善適合度值則停止，則規則庫內之所有規則即為最佳規則。

為了要發展一套以 GFLC 為基礎的號誌控制系統，一個有效率且能正確描述車流行為的模擬軟體是必要的。有部分研究透過微觀模擬軟體為模擬平台，並藉以訂定一最佳化的號誌控制策略，然而這樣的微觀模擬軟體並不適合用來評估基因演算法的模式訓練。基此，本研究採用中觀範疇的混合格位傳遞模式(MCTM)，除了可以有效率的學習 SGFLC 外，更能正確的描述都市地區道路車輛混合之交通行為。

本研究考慮汽車及機車在綠燈時段之交通量(*TF*)及紅燈時段之等候長度(*QL*)為狀態變數，綠燈延長時間為控制變數，總車輛延滯(*TVD*)為評估指標，研擬一 SGFLC 最佳號誌控制方式。為了證明本研究提出模式之績效，在獨立路口部分，比較 2 種定時號誌及 3 種適應性號誌控制，結果顯示 SGFLC 模式之績效最好，此外，當交通流量變化較大時，SGFLC 模式之控制績效也較其他模式為佳。在連續路口部分，不論在何種連鎖策略下，SGFLC 之控制績效也比其他模式好，證明本研究所提出之模式具有效率、強健及可應用之特性。

另外，在路廊的號誌控制部分，眾所皆知的是當連鎖的路口越多，其控制績效就會受到影響，因此，有部分研究試圖透過分群方式，來獲得最佳之連鎖號誌控制的數目，而此分群的概念對於如何將本研究所構建之模式擴展應用到整個路網的控制是非常重要的，因此在一個廊道中，究竟有多少路口應該被連鎖，也是另一個值得被研究的議題。本研究結合 SGFLC 與 GAs 方法，針對一長路廊應連鎖的路口數進行分群，實驗結果顯示，本研究提出之混合模式確實可以有效增加路廊總通過車輛數。

關鍵字：適應性號誌控制、基因模糊邏輯控制器、逐步學習演算法、混合格位傳遞模式

Genetic Fuzzy Logic Signal Control with Mixed-Traffic Cell Transmission Modeling

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Abstract

On-line traffic signal control typically feeds the real-time traffic data, collected by the sensors, into a build-in controller to produce the timing plans. Thus, it can provide signal-timing plans in response to real-time traffic conditions. Because of its flexibility, applicability and optimality, adaptive signal control tends to be the mainstream of signal controls nowadays. The well-known adaptive signal controllers employ mathematical equations or models to determine "crisp" threshold values as the cores of control mechanism; thus, the control performance could be negatively affected by the uncertainty of traffic conditions. Since a fuzzy control system has excellent performance in data mapping as well as in treating ambiguous or vague judgment, many works have employed fuzzy set theory to develop fuzzy logic controllers (FLC). In FLC systems, both inference engine and defuzzification have been consistently used in previous literature; however, methods for formulating the rule base (logic rules) and data base (membership functions) are subjectively preset, not optimally solved. Employing GAs to construct an FLC system with learning process from examples, hereafter termed as genetic fuzzy logic controller (GFLC), can not only avoid the bias caused by subjective settings of logic rules or membership functions but also greatly enhance the control performance. However, to simultaneously or sequentially learn of logic rules and membership functions may require a rather lengthy chromosome and large search space, resulting into poor performance, a long convergence time and unreasonable learning results (i.e. conflicting or redundant logic rules, irrational shapes of membership functions).

To avoid abovementioned shortcomings, based on the iterative GFLC (Chiou and Lan, 2005), this study proposes a stepwise genetic fuzzy logic controller (SGFLC) to learn both logic rules and membership functions. At each learning process, the proposed algorithm selects one logic rule which can best contribute to the overall performance controlled by previously selected logic rules combined with this selected rule. Such a selection procedure will be repeated until no other rule can ever improve the control performance. Therefore, the incumbent combination of logic rules is the near optimal learning results.

In order to develop a SGFLC-based signal control requires an efficient traffic simulation model to replicate traffic behaviors and to determine the performance of the control logic.

Many studies use microscopic traffic simulation software to simulate the urban signal control and implement the optimized signal policy. However, such simulation software is rather time consuming, making it better for evaluating the control performance for a given signal control model but not suitable for the evolution of genetic generations for model training. For the learning efficiency of SGFLC and the capability in capturing traffic behaviors of Asian urban streets where mixed traffic of cars and motorcycles are prevailing, the mixed traffic cell transmission model (MCTM) is introduced to replicate the traffic behaviors.

This study considers traffic flows and queue lengths of cars and motorcycles as the state variables and extension of green time as the control variable, towards the minimization of total vehicle delays. To investigate the control performance of the proposed SGFLC model, comparisons of two pre-timed timing plans and three adaptive signal timing models are conducted at an isolated intersection. Results show our proposed SGFLC model performs the best. Moreover, as traffic flows vary more noticeably, the SGFLC model performs even better than any other models.

In the case of a 3-intersection arterial under four coordinated signal systems i.e., simultaneous, progressive, alternate and independent, both experimental example and field case study show that the proposed SGFLC model can perform better than any adaptive control models, suggesting that the proposed SGFLC signal control model is efficient, robust and applicable.

Moreover, it is well-known that the control performance of signal coordination would be greatly degraded as the number of coordinated intersections increases. Thus, this study also combines SGFLC with GAs for optimizing the number of coordinated intersections along a long corridor. The experimental example shown that the proposed hybrid model can increase total throughput along the corridor through an optimal coordinated intersections.

KEY WORDS: adaptive signal control, genetic fuzzy logic controller, stepwise learning algorithm, mixed-traffic cell transmission model.

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Chapter1 INTRODUCTION

This chapter consists of three sections. Section 1.1 addresses the research background and motivation of this study. The research purposes and flowchart are introduced in Sections 1.2 and 1.3, respectively.

1.1 Background and Motivation

Traffic signal control is one of the most important strategies of traffic management in densely populated and highly motorized areas. Efficient and effective traffic signal control systems can not only curtail traffic congestion caused by insufficient of road capacity but also greatly reduce fuel consumption, emissions and even increase traffic safety.

Traffic signal control models can be divided into two major categories: pre-timed signal control and on-line signal control. Pre-timed signal control models optimize signal timing plans mainly based on historical traffic data. The pre-timed signal control models frequently resulted in the inefficient usage of intersection capacity because of their inability to adjust the timing plans according to the variations of traffic flow. In contrast, on-line signal control models typically feed the real-time traffic data, collected by the sensors, into a built-in controller to determine the timing plans in response to real-time traffic conditions. It is well known that the on-line models can perform better than the pre-timed models, if the on-line models have been carefully and correctly designed.

Actuated signal control, dynamic signal control, and adaptive signal control are examples of on-line control. Because of its flexibility, applicability and optimality, adaptive signal control tends to be the mainstream of signal controls nowadays. The well-known adaptive signal controllers, such as SCOOT, SCATS, and OPAC, employ mathematical equations or models to determine “crisp” threshold values as the cores of control mechanism; thus, the control performance could be negatively affected by the uncertainty of traffic conditions.

Since a fuzzy control system has excellent performance in data mapping as well as in treating ambiguous or vague judgment (Teodorovic, 1999), many recent works have employed fuzzy set theory to develop fuzzy logic controllers (FLC), also known as fuzzy control system, fuzzy inference system, approximate reasoning, or expert system. The applications of FLC to signal control are to determine the signal phasing and timing plans, including priority of phases, cycle length and split, by utilizing the real-time traffic data, such as arrival flow rate, occupancy, queue length and speed, collected by detectors. Learning the logic rules and tuning the membership functions are the two key components for a FLC system. Genetic algorithms (GAs) have been proven suitable for solving both combinatory optimization and parameter optimization problems (i.e., rules selection and parameters calibration). Employing GAs to construct a FLC system with learning process from examples, hereafter abbreviated as genetic fuzzy logic controller (GFLC), not only can avoid the bias caused by subjective settings of logic rules and membership functions but also can greatly enhance the control performance.

In doing so, Chiou and Lan (2005) proposed a GFLC model to iteratively learn the logic rules and tune membership functions. The applicability of the model has been proven by a series of studies, such as Chiou and Lan (2004), Chiou and Wang (2005), Chiou *et al*. (2003; 2005; 2007). However, the GFLC model proposed by Chiou and Lan's (2005) tends to select too many logic rules which are mutually conflicted and redundant, making the interpretation and post-optimization adjustment impossible. Based on this, this study aims to propose a modified GFLC model which can overcome these problems and achieve even better performances in signal control.

In the other hand, how to efficiently evaluate the performance of signal control models by using a traffic flow model is an important issue. In literature, CORSIM, AIMSUN, VISSIM, MITSIMLab, INTEGRATION and PARAMICS are commonly used to evaluate the control performance of signal control models. However, it would be too time-consuming to use these simulation software packages for the evolution of genetic generations; thus, the macroscopic traffic simulate model-CTM proposed by Daganzo (1994, 1995) is used in this study instead. Additionally, since the original CTM model is designed for simulating the pure traffic, to acknowledge that motorcycles are prevailing in many Asian urban streets, in order to capture the real traffic behavior under mixed traffic condition, the mixed traffic flow model should be considered.

Moreover, it is well-known that the control performance of signal coordination would be greatly degraded as the number of coordinated intersections increases. Thus, numerous studies (e.g. Wong, 1997; Kosonen 2003; Schmocker *et al*., 2008) attempted to determine the optimal number of neighboring intersections to be coordinated. The concept to cluster the coordinated intersections is especially important for the application of the proposed model to a large-scale network. How to optimally determine which and how many signalized intersections have to be coordinated is another topic worthy of studying.

1.2. Research Purposes

Based on the abovementioned motivations, the major research purposes of this study can be narrated as follows:

1. Based on the GFLC model proposed by Chiou and Lan (2005), to propose a modified GFLC model, which can more efficiently learn of logic rues and tune the membership functions.

2. To use of a mixed traffic cell transmission model to facilitate the learning of the proposed modified GFLC model with considering different state variables.
3. To develop a systematic method to determine the clusters of coordinated intersections for a long arterial based on the modified GFLC model.
4. To investigate the performance and applicability of the proposed model, exemplified examples and case study on isolated intersections as well as coordinated arterials are conducted.
5. To show the performance of the proposed model, comparisons to other pre-timed signal timing plans and adaptive signal control models are also conducted.

1.3 Research Flowchart

Figure 1.1 presents the research flowchart of this study. As shown in Figure 1.1, each of research procedures is further elaborated below.

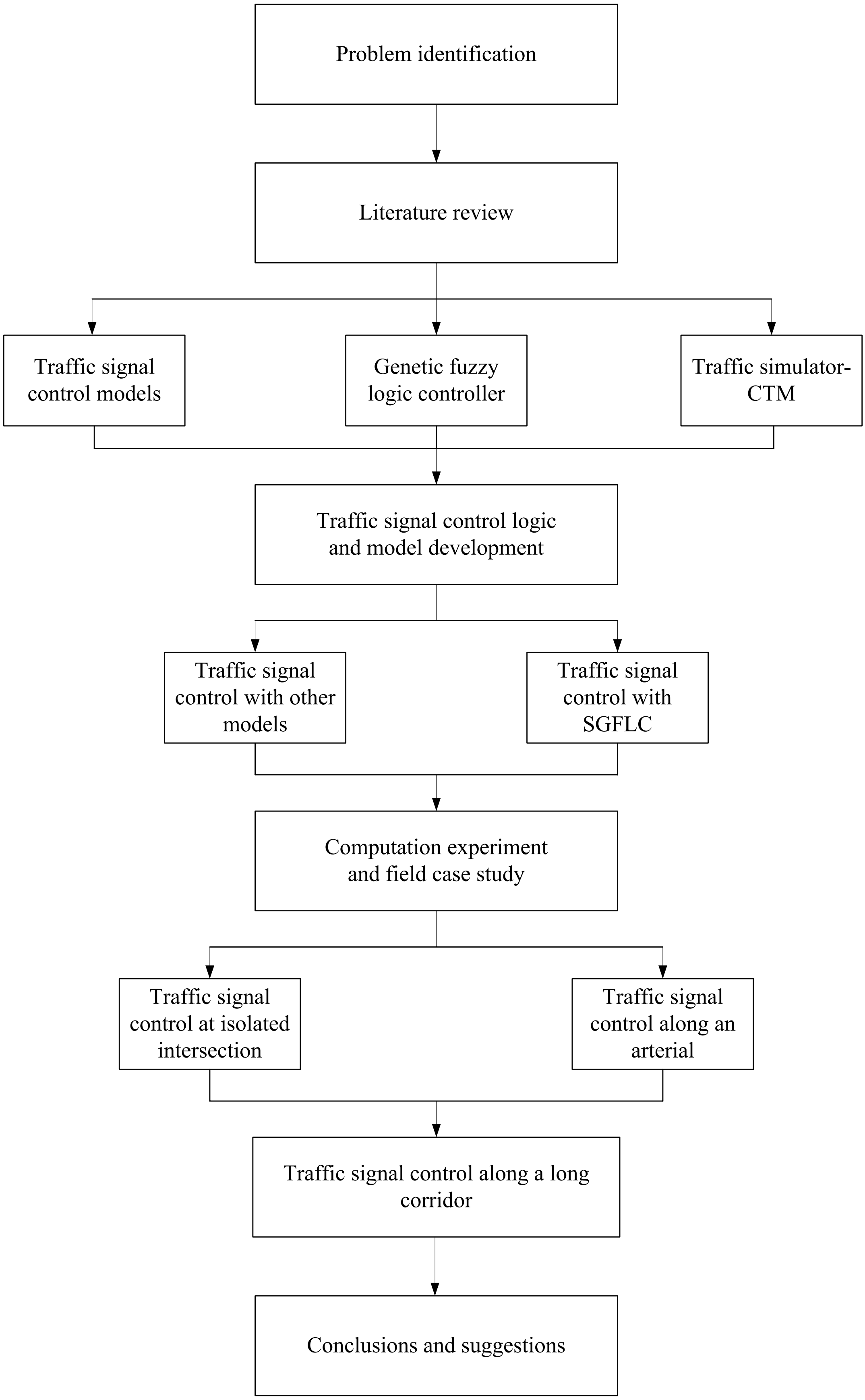


Figure 1.1 Research flowchart

1. Problem identification

The first step is to identify the purposes and scopes of this study, and to address problems which need to be explored.

2. Literature review

The second step is to review the traffic signal control models and related research. The cell transmission model and mixed traffic flow method and related works are conducted. The FLC relative methods, including GA, and GFLC, used in this study are also reviewed. This step helps to realize the current state of development of traffic signal control and to facilitate the theoretical modeling.

3. Traffic signal control logic and model development

A traffic signal control mechanism based on FLC is developed in this procedure. Afterwards, the model integrating GA into the FLC by a stepwise learning algorithm is developed In addition, this study also introduces other signal control models including pre-time and adaptive method, respectively.

4. Computational experiment and validation

To investigate the effectiveness of the proposed SGFLC models, the traffic signal control with the proposed SGFLC is first applied at an isolated intersection under an exemplified example and a field case. Sensitivity analyses are also conducted to examine the robustness of the proposed models. To generalize the implementation environment, the traffic signal control with SGFLC is then carried out along an arterial with three consecutive intersections. Similarly, an exemplified example, a field case, and sensitivity analyses of them are also conducted. In this procedure, the exemplified examples and field cases are simulated.

5. Traffic signal along a long corridor

The proposed models also implement along a long corridor. This study address SGFLC controller along a arterial with a total of 15 intersections. The binary genetic algorithm was used to determine clusters of coordinated intersections. To investigate the effectiveness of the proposed SGFLC models with binary coding GA is compared with other general intersection clustering methods referred to the textbooks of traffic control.

6. Conclusions and suggestions

The major findings in the processes of model formulation and model validation are summarized. The strengths and weaknesses of the proposed models will be thoroughly discussed. At last, some suggestions for future studies are identified.

Chapter 2 LITERATURE REVIEW

This chapter firstly reviews the traffic signal control models and related researches. On the other hand, genetic fuzzy logic controller and related researches also conducted in second part. The concepts of the macroscopic traffic flow simulator, cell transmission model (CTM), adopted in this study briefly elaborated and reviewed as following. Finally, a summary is followed.

2.1 Traffic Signal Control Models

2.1.1 Signal control methods

1. Classification of signal control methods

(1) Pre-timed control

Traffic signals in use today typically operate based on a pre-set timing schedule. The most common traffic control system used in the USA is the Urban Traffic Control System (UTCS), developed by the Federal Highway Administration in the 1970s. UTCS generates timing schedules off-line using manual or computerized techniques. These predetermined timing schedules are implemented by the system according to the time of the day. The timing schedules are typically obtained by either maximizing the bandwidth (which means the width of the through-band in seconds indicating the period of time available for traffic to flow within the band) on arterial streets or minimizing a disutility index that is generally a measure of delay and stops. Computer programs such as MAXBAND (Little *et al*, 1981) and TRANSYT (i.e. Robertson, 1969) are well established means for performing such optimization. The off-line approach used by UTCS cannot respond adequately to unpredictable changes in traffic demand.

(2) Traffic-responsive control without optimization

These are the adaptive control schemes where the signals are changed based on the actuation of stop-line detectors and minimum/maximum green times. This type of control responds to traffic but attempts no optimization, network-wide or local.

Dynamic Table Look-Up or Dynamic Pattern-Matching Traffic Control is classical strategy in this classification. The real-time traffic data, collected by the sensors in the time period, transfer to urban control center. The control center collects and identifies data to match the appropriate timing plan, according to the incumbents timing plan database. The interchange controller implements an appropriate timing plan which receives from the control center. This strategy not only can operate with the traffic control center but also can practice in isolated intersections, arterials and network-wide with local group controller and vehicle detectors.

Another control strategy in this classification is Dynamic Timing Computation or Dynamic Pattern-Computing Traffic. Simulates to Dynamic Table Look-Up, this method also collected real-time traffic data by detector. The control center not only collects and identifies data but also predicts the traffic condition in next period. According to the prediction result, the timing plan analysis software can calculate a new timing plan to fit the traffic flow. The new timing plan will send to controller in intersection or local group controller. The prediction capability and data analysis procedure are key components of this strategy.

(3) Traffic-responsive control with optimization

These techniques calculate control parameters according to prevailing traffic conditions. They typically respond to changing traffic demand by performing incremental optimization. This control method also improves Dynamic Table Look-Up and Dynamic Timing Computation in the response of incident, the failure of traffic flow prediction and negative performance when timing plan changed. The most notable of these Adaptive Traffic Control models are SCATS, SCOOT and SCATS…etc.

The characteristics, advantage and disadvantage of strategies/models mentioned above are compared as Table 2.1.

Table 2.1 Comparisons of different traffic signal control strategies.

Items	Pre-timed	Traffic-responsive control without optimization	Traffic-responsive control with optimization
Timing plan product			
Collect traffic data	×	Time period	Time period
Flow forecast	×	Time period or ×	×
implement	Off-line	On-line	On-line
Timing change	Time of day	Dynamic table of computation	adaptive
System capability			
Approach intersection controller	×	✓	✓
Incident treatment	Non-flexible	flexible	Very- flexible
Accident detector	×	✓	✓
Advantage	Cost down Maintain easy Install fast	Response traffic Detect real traffic	Response traffic Avoid failure Detect real traffic Response incident
Disadvantage	Not response traffic Not response incident Not to change timing plan	High cost Forecast traffic Response Incident slow	High cost Need to coordinate

2. Related studies

The most common approach to signalization design is to determine settings for a fixed-cycle signal timing plan that minimizes the average delay per vehicle by car assuming constant arrival rates (Miller, 1963; Webster, 1958). For pre-timed signals the most well-known research was performed by Gazis and Potts (1963) and by Gazis (1964) for a system of two oversaturated intersections in succession. Later researchers (Burhardt, 1971; Gartner, 1983) based their work on Gazis' theory and further extended it for more intersections. Dunne and Potts (1964) developed time-varying control algorithms for an undersaturated intersection with constant arrivals which guarantee that, for any initial state, the system eventually reaches a limit cycle for which the equilibrium average delay per car is a minimum. In all these models, the control policy is not responsive to the dynamics of the traffic flow process since there is no traffic flow model or real-time traffic flow information involved. For real-time control, several algorithms have been proposed (Cremer and Schoof, 1990; Gartner *et al*., 1992; Gordon, 1969; Green, 1968; Lee, Crowley and Pigantaro, 1975; Michalopoulos and Stephanopolos, 1977; Miller, 1965; Papageorgiou, 1983; Ross, Sandys and Schlaefll, 1970). For example, Miller (1965) considered an intersection with heavy traffic and assumed that at time *t* the signal is green on primary approach. At this time the controller can make a binary decision, i.e. to change the signals immediately, or after an extension of one unit of time. However, Miller did not consider the intersection of adjacent intersections, and thus did not include the downstream delays in determining an optimal extension strategy. Ross *et al*. (1970), based their work on a philosophy similar to that of Miller, developed a computer control scheme for traffic-responsive control of a critical intersection that not only minimizes the total delay of all users of the intersection, but also minimizes the total delay accumulated at downstream intersections. Moreover, Longley (1968) proposed a control scheme for a two-phase congested intersection employing a `queue balancing' strategy. This strategy seeks to hold a particular linear function of the intersection queues to a value of zero by adjustment of the green time split.

Lee *et al*. (1975) also considered queues rather than delays as the objective of the control and developed another semi-empirical strategy called ``Queue Actuated Signal Control". This is a control policy where an approach receives green automatically when the queue on that approach becomes equal to or greater than some predetermined length, regardless of the conditions on the conflicting approaches. The policy assumes that no two conflicting approaches reach the upper bound specified for them simultaneously.

Another approach to critical intersection control has been suggested by Gordon (1969). Gordon did not attempt to minimize delay at the intersection but rather to maintain a constant ratio of the queue lengths on opposing approaches. The cycle length is assumed constant and the splits are changed according to the demand so that the ratio of the actual queues to the maximum link storage space on both phases is equal.

Finally, Michalopoulos and Stephanopolos (1977) proposed an optimal control policy for both pre-timed and real-time control. His control policy was to minimize total system delay subject to queue length constraints.

However, it should be noted that most of the control methods mentioned above suffer from complex computational requirements described as above, and from the lack of intersection-to-intersection traffic flow models.

2.1.2 Adaptive traffic signal control

Among online or adaptive approaches, those that collect real-time traffic information from detectors and use it to calculate up-to-date signal settings for implementation pertain to responsive control; those that use real-time traffic information to select a preset signal plan according to the best match with the detected traffic pattern pertain to plan selection. Several well-known signal calculation packages are reviewed here: their characteristics are summarized in Table 2.2.

SCOOT (Hunt et al., 1982) and SCATS (Luk, 1984) are basically online variants of off-line optimization strategies. Manual engineering work is required to update traffic data and feed them into an off-line optimizer, for example TRANSYT (Vincent et al., 1980), for the preparation of a library of plans that apply to different periods of a day and days of a week. The ultimate performance of such systems depends on the accuracy of the database and its conformity to software requirements. The online capability then enables the selection of the most appropriate plan from the library according to detected traffic, adjusts offsets between adjacent intersections to facilitate traffic flow, and makes small adjustments to the signal plan. SCOOT reduces delay to vehicles by 12% when compared to the plans from TRANSYT. SCATS produces 23% reduction in travel time in comparison with uncoordinated operations.

DYPIC (Robertson and Bertherton, 1974), OPAC (Gartner, 1983) and PRODYN (Henry et al., 1983) are successive developments in dynamic traffic signal controller. DYPIC is actually a backward dynamic programming approach that serves only for analytical purpose. An empirical function of quadratic form is derived from the DYPIC study to form a key feature of a heuristic solution intended for practical uses. The heuristic solution adopts the concept of rolling horizon, which implies that: first, a planning horizon is split into a "head" period with detected traffic information and a "tail" period with predicted traffic information. Secondly, an optimal policy is calculated for the entire horizon, but is only implemented for the "“head" period. Finally, when the next time step arrives and new information becomes available, the process rolls forward and repeats itself. Gartner (1983) provides a detailed description of rolling horizon approach in his study of OPAC. However, OPAC does not abide by the principle of optimality adherent to dynamic programming; rather it uses optimal sequential constrained search (OSCO) to plan for the entire horizon, and employs terminal cost to penalize queues remaining in the system after the horizon. OPAC in both simulation and field tests reduces 5-15% vehicle delay from existing traffic-actuated methods, with most of the benefits coming from situation of high degree of saturation. The concerns with OPAC are that the restrictions in OSCO search reduce the flexibility of decision making, and a long planning horizon (60 s) raises practical questions about optimization far into the future on the basis of predicted information, when the decisions planned for the 'tail' may never the implemented. PRODYN, also adopting rolling horizon approach, optimizes timings via a forward dynamic programming (FDP). To avoid computing Bellman's equation at many grid points that eventually poses the problem of dimensionality, the FDP is particularly designed so that it aggregates state variables into a few subsets, and the value of being in a subset is only evaluated when it is actually being arrived at. A value function presenting the future cost in the FDP is directly adopted from Robertson and Bretherton's work. By evaluating all the subsets that can be reached, the FDP calculates the optimal trajectory of control policy in the planning horizon (75 s). The process then rolls forward one step in time. Experiments (Henry, 1989) show that PRODYN yields an average gain in total travel time of 10% with at 99.99% significance.

UPTOPIA (Urban Traffic Optimization by Integrated Automation) (Mauro and Di Taranto, 1989) is a hybrid control system that combines online dynamic optimization and off-line optimization. This is achieved by constructing a system hierarchy with an area level and a local level. The area controller generates reference plan, and local controllers adapt this reference plan and dynamically coordinate signals in adjacent intersections. The rolling horizon approach is again used by local controllers to optimize performance, and the planning horizon is 120 s, with the process being repeated every 3 s. To automate the process of updating reference plans, which are generated by TRANSYT, an AUT (Automatic Updating of TRANSYT) module is developed. AUT first collects traffic data continually from the detectors in the network. The data are processed to calculate traffic flow pictures for different periods of the day. The model predicts the traffic flow profiles for calculating new reference plans. Afterwards, AUT prepares the data for TRANSYT calculation and starts TRANSYT optimization for selected effects. The benefits recorded after the implementation of UTOPIA show an increase of 15% in average speed for private vehicles and 28% for public transport with priority.

MOVA (Vincent and Peirce, 1988) is the only one in this review package which's purposely designed for isolated intersections. The system generates signal timings cycle-by-cycle. The timings vary continuously according to the latest traffic condition. Upon changing signal stage, MOVA uses vehicle gap detected through pairs of upstream detectors to terminate green extension. The criterion for extension is whether the gap reaches certain critical values. There are two operational modes specified for uncongested and congested conditions. In the uncongested mode, delay and stop are minimized, while in the congested mode, capacity is maximized. MOVA evaluates its signal plans every half second.

Table 2.2 Summary of different design models for adaptive traffic signal control.

Program	Traffic data	Decision on signal settings	Signal cycle	Signal coordination	Original county	Objective for optimization	Server mechanism
OPAC	Online data from upstream detectors	Change of current signal settings Rolling forward	Acyclic	Through traffic profile	USA	Delay	Decentralized
UTOPIA	Online data from upstream detectors	Green start times, durations and offset	Required	With offset optimization	Italy	Stops and delay	Centralized
SCATS	Online data from stop line (downstream) detector	Pre-calculated signal plan selection	Required	With offset optimization	Australia	Capacity	Centralized
SCOOT	Online data from upstream detectors	Adjustment of whole signal plan	Required	With offset optimization	UK	stops, delay and congestion	Centralized
PRODYN	Online data from pair of upstream detectors	Change of current signal settings	Acyclic	Possible	France	Total delay	Decentralized
MOVA	Online data from a single upstream detector	Green extension or not	N/A	Nil	UK	stop, delay and capacity	Decentralized
DYPIC	off-line basis and prefect information	complete signal settings	Acyclic	Nil	UK	Delay	Decentralized

2.2 Genetic Fuzzy Logic Controller

The proposed GFLC comprises two methods: Fuzzy Logic Controller (FLC) and Genetic Algorithm (GA).

2.2.1 Fuzzy logic controller

1. The concepts of FLC

The underline theory for the FLC system, first proposed by Zadeh (1973), is to use fuzzy logic rules to form a control mechanism to approximate expert perception or judgment under given conditions. This system is also termed as fuzzy control system, or fuzzy inference system, or approximate reasoning, or expert system. The FLC is a rule-based system that uses fuzzy linguistic variables to model human rule-of-thumb approaches for problem solving, and thus overcome the limitation that classical expert systems may meet because of their inflexible representation of human decision making. The major strength of a FLC also lies in the way a non-linear output mapping of a number of inputs can be specified easily using fuzzy linguistic variables and fuzzy rules (Chin and Qi, 1998). The framework of FLC is depicted in Figure 2.1. A typical FLC system composes of four major components including rule base, data base, inference engine, and defuzzification. They are briefly explained in the following.

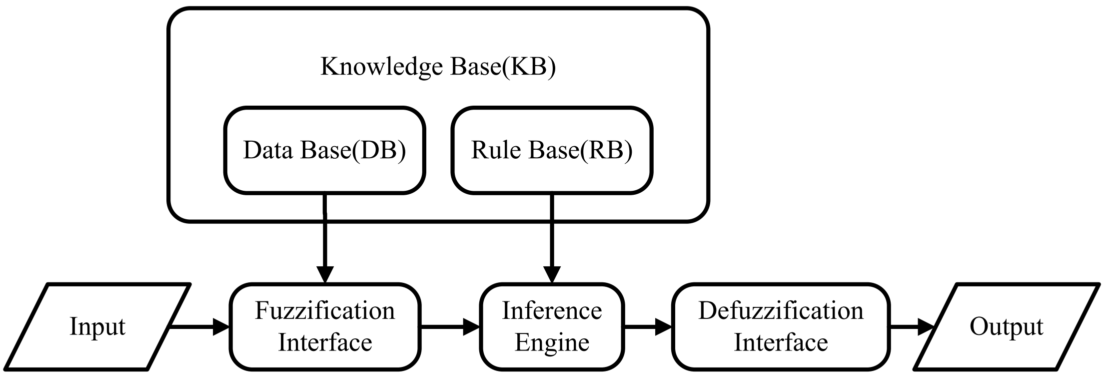


Figure 2.1 Framework of FLC

(1) Rule base (RB).

The RB is composed of finite IF-THEN rules, from which an inference mechanism is formed. A standard form of RB with M fuzzy rules is represented as:

Rule 1：IF $x_1 = A_{11}$ AND $x_2 = A_{12}$ AND … AND $x_N = A_{1N}$ THEN $y = B_1$

Rule 2：IF $x1 = A_{21}$ AND $x_2 = A_{22}$ AND … AND $x_N = A_{2N}$ THEN $y = B_2$

.

.

.

Rule M ∶ IF $x_1 = A_{M1}$ AND $x_2 = A_{M2}$ AND … AND $x_N = A_{MN}$ THEN $y = B_M$

where $x_1,\ldots, x_N$ are N state variables and y is a control variable. A_{i1} ,…, A_{iN} and B_i (i=1,...,M) are respectively the linguistic variables for $x_1,\ldots, x_N$ and y in the universe of discourse of $U_1,\ldots,U_n$ and V. Taking the driving speed as an example, the linguistic degrees can be very fast, fast, normal, slow and very slow. The more general form of the fuzzy rules listed above is: IF premise THEN consequent. The left-hand-side of the rules, the premise or so-called the antecedent, is associated with the fuzzy controller inputs (or called state variables). The right-hand-side of the rules, the consequent, is associated with the fuzzy controller outputs (or called control variables). Each antecedent can be composed of the conjunction of several state variables; however, each consequent is usually formed by one control variable.

(2) Data base (DB).

The DB is formed by the specific membership functions of linguistic variables A_{i1} ,…, A_{iN} and B_i that transform crisp inputs into fuzzy ones. Triangle, trapezoid and bell-shaped membership functions are commonly used.

(3) Inference engine.

The operators within the fuzzy rules form the inference engine. Generally, fuzzy rules use AND (taking minimum value) or OR (taking maximum value) as connecting operators between state variables.

(4) Defuzzification.

For making a decision, defuzzification is the synthesis of inference results of all activated fuzzy rules into crisp outputs. Mean of maximum method, center of gravity method, Tsukamoto's method, and weighted average method are commonly used. The diagrammatic representations of these defuzzification methods are illustrated in Figure 2.2.

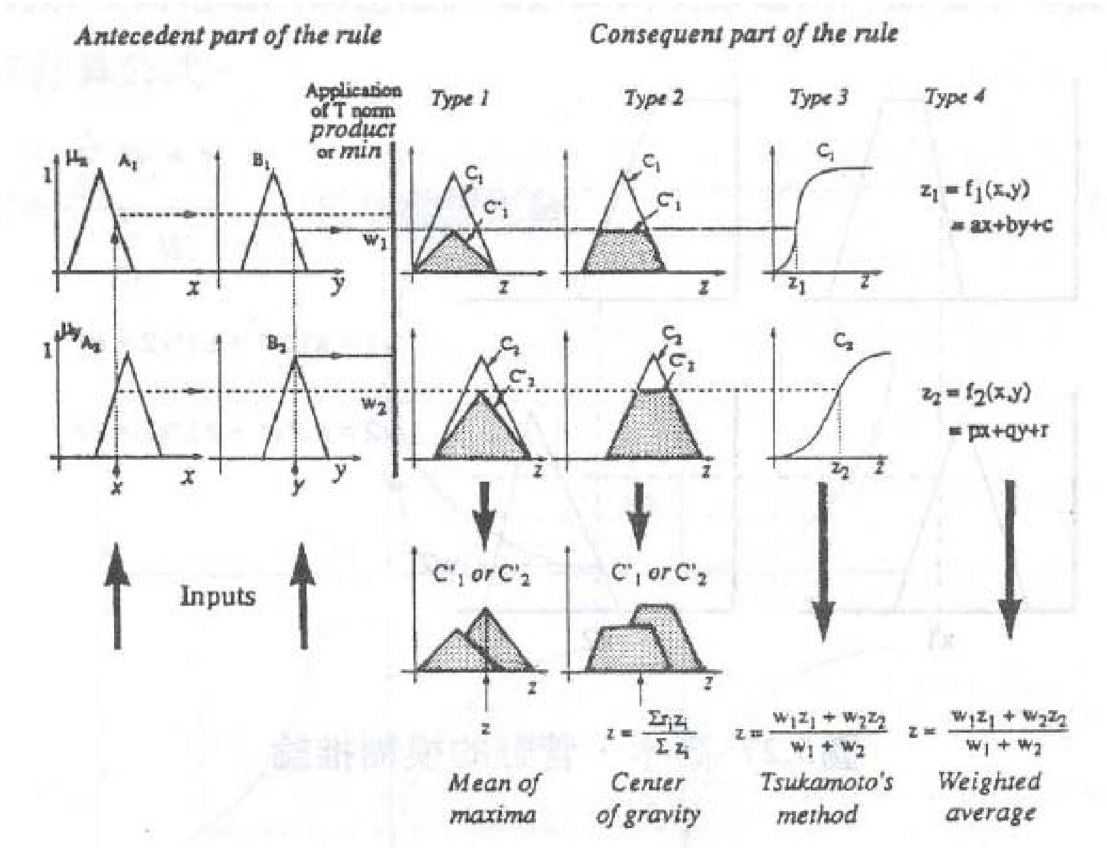


Figure 2.2 Diagrammatic representations of defuzzification methods
Source: Passino and Yurkovich (1997).

2. The applications of FLC

The applications of FLC to signal control are to determine the signal phasing and timing plans, including priority of phases, cycle length and split, by utilizing the real-time traffic data, such as vehicle arrival or arrival rate, occupancy, queue length, and speed, collected by detectors. Pappis and Mamdani (1977) first applied FLC to signal control by using 25 logic rules with three states variables: elapsed time, vehicle arrivals, and queue length to determine the extension of green time. Their results show that the FLC signal control has total vehicle delays 10 to 21% less than an actuated signal control. Nakatsuyama *et al.* (1984) further applied FLC to signal control on the one-way arterial consecutive intersections. Favilla *et al.* (1993) employed 11 logic rules with two state variables, vehicle arrivals in the green phase and queue length in the red phase, to control the extension of green time. Hoyer and Jumar (1994) used 72 logic rules with 10 state variables to choose the next phase and to determine its green time. According to the traffic flows, Kim (1997) proposed 23 logic rules, seven for high, nine for medium and seven for low traffic volumes, to control the green time extension in different approaches. Mohamed *et al.* (1999) established a two-stage FLC model. The first stage is to evaluate the traffic intensity in the competing directions by 16 logic rules with traffic flows or queue lengths as the state variables. The second stage is to decide the extension or termination of current phase by 16 logic rules with two state variables, traffic intensities in green and red phases. Their results indicate that FLC model has delays 9.54% less and stopped vehicles 1.29% less than the actuated signal control. Niittymäki *et al.* (2001) also developed a two-stage FLC model. Their first stage is to evaluate the traffic conditions by three logic rules with two state variables, traffic flow and occupancy. The second stage is to determine the green time extension by 20 logic rules with two state variables, vehicle arrival in green phase and queue length in red. The results from both simulation and field test reveal that FLC model has outperformed over the actuated signal control. Chou and Teng (2002) presented 9 logic rules with four inputs, queue lengths of each directions of the junction, to define the extension time of the current green phase. Based on the compared items, the proposed model possesses some advantage characteristics, including using different antecedents, applicable to any number of junctions, integrating every junction's status, requiring fewer control rules, needing fewer inference time, and taking street's distances into account. Kosonen (2003) developed multi-agent fuzzy signal control model. The ideal of the presented control technique, each signal operates individually, negotiating with other signals about the control strategy. The agents make decision based on fuzzy inference that allows a combination of various aspects like fluency, economy, environment and safety. The result of proposed method compared with detector logic and with mathematical optimization modes indicate that the performance of average delay better than detector logic control but worse than the mathematical optimization modes especially with high traffic in the mourning rush hours in Sweden. Murant and Gedizlioglu (2005) proposed fuzzy logic multi-phased signal control model to determine both the phase green time and phase sequences. The signal time controller is to determine the signal timing by 65 logic rules with three state variables, the longest of the queues in red signal, arrivals to junction during green signal and green time indicator. Another is to decide phase ordering of current phase by 37 logic rules with three variables, longest of the queues during red signal, longest vehicle queue in next phase and red time of the longest queue. The result shows that the proposed model compared with traffic-actuated control decrease delays of vehicles between 15% and 50% when traffic volumes are more than 500 vehicles per hour for the three-phased controlling situation. Results of comparisons for the four-phased control situation and traffic volumes are more than 400 vehicles per hour; the model has some advantages over the traffic-actuated control and improves the performance values by about 17.6%.

Table 2.3 provides a summary of the application of fuzzy logic-based traffic signal control. In FLC systems, both inference engine and defuzzification have been consistently used in previous literature; however, methods for formulating the rule base and data base are subjectively preset, not optimally solved.

Table 2.3 Summary of the evolution of fuzzy logic based traffic signal control.

Author(s)	Area of contributions
Pappis and Mamdani (1977)	They presented the implementation of a fuzzy logic controller in a single intersection of two one-way streets without turning traffic
Nakatsuyama *et al*. (1984)	They applied fuzzy logic to control two adjacent intersections with one-way movements for determining the extension or termination of the green signal for the downstream intersection based on the upstream traffic
Favilla *et al*. (1993)	They presented the implementation of a fuzzy logic controller which is composed of a FLC, a State Machine and an Adaptive Module for a single junction having multiple lanes
Chou and Teng (2002)	They presented a fuzzy logic based traffic junction signal controller (FTJSC) which is applicable to multiple junctions and multiple lanes
Hoyer and Jumar (1994	They used FLC to choose the next phase and to determine its green time.
Kim (1997	According to the traffic flows, proposed logic rules to control the green time extension in different approaches.
Mohamed *et al*. (1999	They established a two-stage FLC model to evaluate the traffic conditions and to decide the extension or termination of current phase.
Niittymäki *et al*. (2001)	They also developed a two-stage FLC model to evaluate the traffic conditions to determine the green time extension.
Kosonen (2003)	This search developed multi-agent fuzzy signal control model. The agents make decision based on fuzzy inference that allows a combination of various aspects like fluency, economy, environment and safety.

2.2.2 Genetic fuzzy logic controller

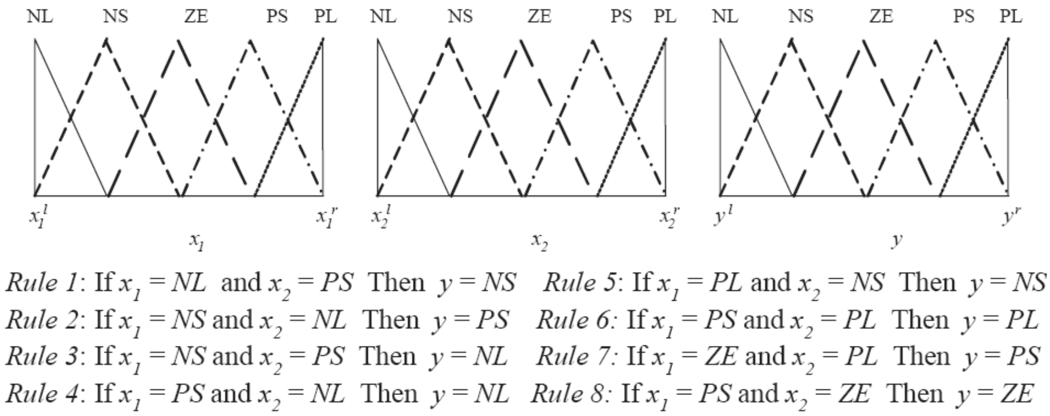
In FLC systems, both inference engine and defuzzification have been consistently used in previous literature; however, methods for formulating the rule base (logic rules) and data base (membership functions) are subjectively preset, not optimally solved. Adjusting the combination of logic rules and membership functions very often requires tremendous efforts, but there is no guarantee to obtain good control performance. Genetic algorithms (GAs) have been proven suitable for solving both combinatory optimization problem (e.g., selecting the logic rules) and parameter optimization problem (e.g., tuning the membership functions). Employing GAs to construct an FLC system with learning process from examples, hereafter termed as genetic fuzzy logic controller (GFLC), can not only avoid the bias caused by subjective settings of logic rules or membership functions but also greatly enhance the control performance.

The GA, first proposed by Holland (1975), is a searching process based on the mechanics of natural selections and natural genetics. GA is a global optimization technique that avoids many shortcomings exhibited in conventional search techniques on a large and complicated search space. Generally, a simple GA contains three basic operators: selection, crossover, and mutation. GA starts with a population of randomly generated solutions (also called chromosomes) determined by genes that are in code term, and advance toward better solutions by applying genetic operators, modeled on the genetic processes occurring in nature. During the iterative procedures, a constant size of population of candidate solution is maintained, and this population undergoes evolution in a form of natural selection (Herrera *et al*., 1998).

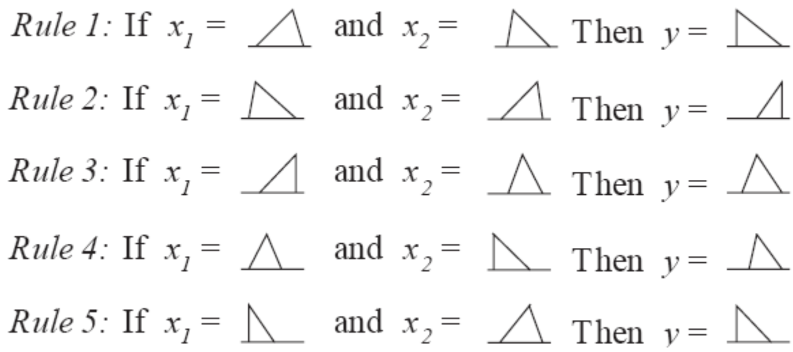
According to the mention above, a considerable number of works relating to GFLC in different areas have been found in recent years. Such GFLC related works can be divided into four categories.

1. Use of GAs to tune membership functions under a given set of logic rules.

Depending on the types of knowledge base, descriptive knowledge base and approximate fuzzy rule base can further be identified as shown in Figure 2.3 The former assumes that membership functions of a specific state/control variable are the same in all logic rules; the latter allows that the membership functions of the same state/control variable can be varied in different logic rules. Therefore, tuning the membership functions of descriptive knowledge base implies calibrating the parameters of membership functions with a fixed number of linguistic degrees for $A_{i1}, \ldots, A_{in}$ and B_i (e.g. Herrera *et al*., 1995, Karr, 1991, Karr and Gentry, 1993, Park *et al*. 1994). Tuning the membership functions of approximate fuzzy rule base means calibrating the parameters in membership functions $A_{i1}, \ldots, A_{in}$ and B_i for each logic rule (e.g. Glorennec, 1997, Herrera *et al*., 1998). The major disadvantages of descriptive knowledge base are the rapid increase in chromosome length as linguistic degrees increase and it needs to consider the reasonableness of relative values among parameters. Nonetheless, this structure has the advantages that the length of chromosome is not related to the number of logic rules and that the meaning of calibrated logic rules could be implicitly interpreted as an expert's judgment and decision. On the contrary, approximate fuzzy rule base has the disadvantages that the length of chromosome grows rapidly as the number of logic rules increases and that it is sometimes difficult to interpret the calibrated logic rules as an expert's judgment and decision. But there is no need to consider the reasonableness of relative values among parameters. The most common shapes of membership functions are triangular, trapezoidal or Gaussian functions. Each shape function has some parameters to be coded and tuned. For instance, the coordinates of cortex and two anchors of a triangular shape need to be determined. To work with reasonable distributions between linguistic fuzzy sets, tuning ranges or more specific shapes, such as fixed width of triangle base, fixed overlapping width between fuzzy sets, and isosceles triangle, are normally assumed. As an example, Gurocak (1999) specifies tuning ranges for shifting the peak locations of the fuzzy sets according to a series of binary genes.



(a) Descriptive knowledge base;



(b) Approximate fuzzy rule base.

Figure 2.3 Type of knowledge base.

Source : Cordon *et al*.(2001)

2. Use of GAs to select logic rules with known membership functions.

Three commonly used encoding methods for selecting the logic rules are identified in the literature. The first method, in Lekova *et al*. (1998), uses one gene, with a binary value, to represent inclusion or non-inclusion of a specific logic rule. The chromosome length depends on the number of potential logic rules. The second method, in Chin and Qi (1998), uses one gene to represent the first part (premise) of a specific logic rule and the following genes to represent the latter part (linguistic degrees of control variable) of the same logic rule. The third method, in Thrift (1991), uses one gene to represent each logic rule and the value of each gene indicates the linguistic degree of control variable for the corresponding logic rule. Contrasting to the first method, the second and third methods impose a constraint that a specific premise cannot map to different linguistic degrees of control variables. The strength of the first method is that all possible permutations of logic rules can be considered; its weakness is that the chromosome might be too long. The strength and weakness of the second and third methods are just contrary to the first method.

3. Use of GAs to learn both logic rules and membership functions simultaneously.

There are two categories of methods to learn logic rules and membership functions simultaneously. The methods of the first category employ genetic learning algorithm to learn both logic rules and membership functions. For instance, Homaifar and McCormick (1995) adopt Thrift (1991) encoding method by using part of a chromosome to represent the composition of logic rules and using each gene of the remaining part to represent the triangle base of each membership function. Xiong and Litz (2002) use binary coding of rule premises and use integer coding of the two anchors of triangular membership functions with the constraint that the right anchor of a membership function is coincided with the left anchor of the next adjacent membership function. Herrera *et al*. (1998) use a chromosome to represent the membership functions of all variables in a logic rule. It is the structure of approximate fuzzy rule base, in which the fitness of GAs cannot be evaluated as the control performance; other criteria must be designed to represent the fitness of chromosome. The articles of mention above use part of a chromosome to represent the composition of logic rules and use the remaining part to represent the shapes of membership functions. The methods of the second category use the hybrid learning algorithms by combining GAs with other algorithms to learn both logic rules and membership functions. For instance, Wang and Yen (1991) use GAs to solve the combination of logic rules and employs Kalman filter to tune the shapes of membership functions. Lin (2004) constructs a genetic algorithm-based neural fuzzy system

(GA-NFS) by employing GAs to tune the membership functions in the precondition part of fuzzy rules and using least-squares estimation to tune the parameters in the consequent part.

4. Use of GAs to learn both logic rules and membership functions in sequence.

Both two- and three-stage procedures are found in learning the logic rules and membership functions sequentially. A two-stage procedure, proposed by Karr (1991), uses GAs to learn logic rules and then uses another GAs to tune the membership functions. Kinzel *et al*. (1994) and Cordon *et al*. (1997) establish a three-stage procedure by presetting an initial pool of logic rules, then using GAs to select logic rules from the pool, and finally using another GAs to tune the membership functions. Chung *et al*. (2003) propose another three-stage hybrid learning algorithm. In the first stage, the fuzzy ART algorithm is used to do fuzzy clustering in the input/output spaces according to supervised training data. In the second stage, GA is used to select logic rules by associating input clusters and output clusters. In the third stage, the backpropagation algorithm is used to tune the membership functions. Chiou and Lan (2005) proposed a bi-level iterative evolution algorithm in selecting the logic rules and tuning the membership functions for iterative genetic fuzzy logic controller (IGFLC). The upper level is to solve the composition of logic rules using the membership functions tuned by the lower level. The lower level is to determine the shape of membership functions using the logic rules learned from the upper level.

The IGFLC selects logic rules and tunes membership functions by GA in sequence. The encoding methods, genetic operators and iterative evolution algorithm for the GFLC model are briefly described as follows.

(1) Encoding method for logic rules

Each logic rule is represented by one gene and its linguistic degree of control variable is indicated by the value of the corresponding gene. Taking two state variables and one control variable as an example, if each variable has five linguistic degrees (NL: negative large, NS: negative small, ZE: zero, PS: positive small, PL: positive large), then the chromosome length is 25. Genes take the integers from 0 to 5, where 0 represents the exclusion of the rules; other numbers indicate the inclusion of the rules and the linguistic degrees of control variable. This encoding method is depicted in Figure 2.4. A chromosome with gene sequence of 0002040010000001000030000, for example, will represent five logic rules being selected:

Rule 1: IF $x_1 = NL$ and $x_2 = PS$ THEN $y = NS$
Rule 2: IF $x_1 = NS$ and $x_2 = NL$ THEN $y = PS$
Rule 3: IF $x_1 = NS$ and $x_2 = PS$ THEN $y = NL$
Rule 4: IF $x_1 = PS$ and $x_2 = NL$ THEN $y = NL$

Rule 5: IF $x_1 = PL$ and $x_2 = NL$ THEN $y = ZE$

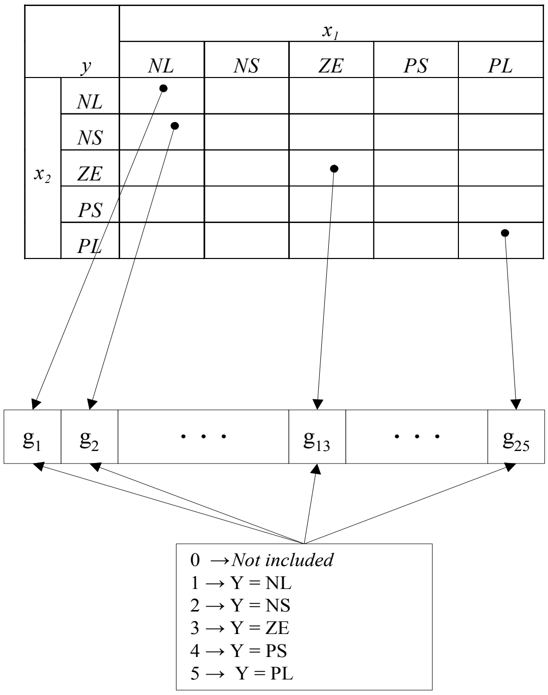


Figure 2.4 Encoding method for logic rules.
Source: Chiou and Lan (2005).

(2) Encoding method for membership function

Consider a triangle fuzzy number and let parameters c_k^r, c_k^c and c_k^l respectively represent the coordinates of right anchor, cortex and left anchor of k^{th} linguistic degree. Then 15 parameters need to be calibrated for a variable with five linguistic degrees. Furthermore, it is assumed that the first and last degrees of fuzzy numbers are left- and right-skewed triangles, respectively, and that the others are isosceles triangles as shown in Figure 2.5. Therefore, a variable with five linguistic degrees has eight parameters to be calibrated and their orders are:

$$c_{\max} = c_5^c = c_5^r \geq c_4^r \geq \begin{matrix} c_5^l \\ c_3^r \end{matrix} \geq \begin{matrix} c_4^l \\ c_2^r \end{matrix} \geq \begin{matrix} c_3^l \\ c_1^r \end{matrix} \geq c_2^l \geq c_1^c = c_1^l = c_{\min} \tag{2-1}$$

$$c_k^c = \frac{(c_k^r + c_k^l)}{2} \text{ , } k=2, 3, 4 \tag{2-2}$$

where c_{max} and c_{min} are the maximum and minimum values of the variable, respectively. The orders between $c_5^{\,l}$ and $c_3^{\,r}$, $c_4^{\,l}$ and $c_2^{\,r}$, $c_3^{\,l}$ and $c_1^{\,r}$ are indeterminate. In order to tune these eight parameters, nine position variables $r_1, \ldots, r_9$ are designed as follows:

$$c_2^l = c_{\min} + r_1 \times \theta \tag{2-3}$$

$$c_1^r = c_2^l + r_2 \times \theta \tag{2-4}$$

$$c_3^l = c_2^l + r_3 \times \theta \tag{2-5}$$

$$c_2^r = \max\{c_1^r, c_3^l\} + r_4 \times \theta \tag{2-6}$$

$$c_4^l = \max\{c_1^r, c_3^l\} + r_5 \times \theta \tag{2-7}$$

$$c_3^r = \max\{c_2^r, c_4^l\} + r_6 \times \theta \tag{2-8}$$

$$c_5^l = \max\{c_2^r, c_4^l\} + r_7 \times \theta \tag{2-9}$$

$$c_4^r = \max\{c_3^r, c_5^l\} + r_8 \times \theta \tag{2-10}$$

where $\theta = \dfrac{(c_{\max} - c_{\min})}{\sum_{i=1}^{9} r_i}$.

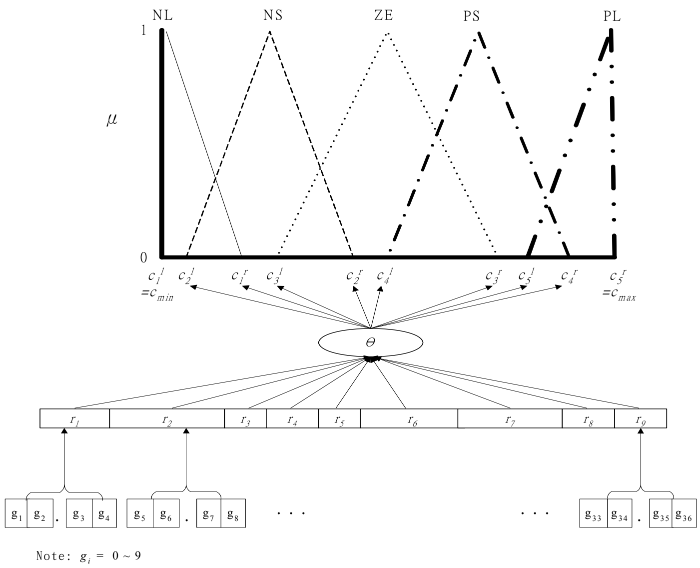


Figure 2.5 Encoding method for membership functions.
Source: Chiou and Lan (2005).

To achieve two significant digits, each position variable is represented by four real-coding genes also depicted in figure 2.6. The maximum value of the position variables is 99.99 and the minimum value is 0. Thus, in the example of two state variables and one control variable (each with five linguistic degrees), the chromosome is composed of 108 genes.

(3) Genetic operators

The max-min-arithmetical crossover proposed by Herrera *et al.* (1995) and the non-uniform mutation proposed by Michalewicz (1992) are employed. In the max-min-arithmetical crossover, let $G_w^t = \{ g_{w1}^t, ..., g_{wk}^t, ..., g_{wK}^t \}$ and $G_v^t = \{ g_{v1}^t, ..., g_{vk}^t, ..., g_{vK}^t \}$ be two chromosomes selected for crossover, the following four offsprings will be generated (Herrera *et al.*,1995):

$$G_1^{t+1} = aG_w^t + (1-a)G_v^t \quad (2\text{-}11)$$

$$G_2^{t+1} = aG_v^t + (1-a)G_w \quad (2\text{-}12)$$

$$G_3^{t+1} \text{ with } g_{3k}^{t+1}=min\{g_{wk}^t, g_{vk}^t\} \quad (2\text{-}13)$$

$$G_4^{t+1} \text{ with } g_{4k}^{t+1}=max\{g_{wk}^t, g_{vk}^t\} \quad (2\text{-}14)$$

where a is a parameter ($0 < a < 1$) and t is the number of generations. In the non-uniform mutation, let $G_t = \{ g_1^t, ..., g_k^t, ..., g_K^t \}$ be a chromosome and the gene g_k^t be selected for mutation (the domain of g_k^t is $[g_k^l, g_k^u]$), the value of g_k^{t+1} after mutation can be computed as follows:

$$g_k^{t+1} = \begin{cases} g_k^t + \Delta(t, g_k^u - g_k^t) & if \quad b = 0 \\ g_k^t - \Delta(t, g_k^t - g_k^l) & if \quad b = 1 \end{cases} \quad (2\text{-}15)$$

where b randomly takes a binary value of 0 or 1. The function $\Delta(t,z)$ returns a value in the range of [0, z] such that the probability of $\Delta(t,z)$ approaches to 0 as t increases:

$$\Delta(t,z) = z(1 - r^{(1-t/T)^h}) \quad (2\text{-}16)$$

where r is a random number in the interval [0,1], T is the maximum number of generations and h is a given constant. In Eq. (2-16), the value returned by $\Delta(t,z)$ will gradually decrease as the evolution progresses.

(4) Evolution algorithm

The iterative evolution algorithm for selecting the logic rules and tuning the membership functions is similar to a bi-level mathematical programming. The upper level is to solve the composition of logic rules using the membership functions tuned by the lower level. The lower level is to determine the shape of membership functions using the logic rules learned from the upper level. Consider an FLC with n state variables $x_1, x_2, \ldots, x_n$ and one control variable y, each with $d_1, d_2., \ldots, d_n$ and d_{n+1} linguistic degrees. Assume that the membership functions of all linguistic degrees to be triangle-shaped. The iterative evolution algorithm is structured as follows:

Step 0: Initialization: $s=1$.

Step 1: Selecting logic rules.

Step 1-1: Generating an initial population with p chromosomes. Each chromosome has $\prod_{i=1}^{n} d_i$ genes, and each gene randomly takes one integer from [$0, d_{n+1}$].

Step 1-2: Calculating the fitness values of all chromosomes based on incumbent shapes of membership functions.

Step 1-3: Selection.

Step 1-4: Crossover.

Step 1-5: Mutation.

Step 1-6: Testing the stop condition. The stop condition is set based on whether the mature rate (the proportion of same chromosome in a population) has reached a given constant η. If so, proceed to Step 2; otherwise go to Step 1-3.

Step 2: Tuning membership functions.

Step 2-1: Generating an initial population with p chromosomes. Each chromosome has $36(n+1)$ genes and each gene randomly takes one integer from [$0, 9$].

Step 2-2: Calculating the fitness values of all chromosomes based on the incumbent combination of logic rules.

Step 2-3: Selection.

Step 2-4: Crossover.

Step 2-5: Mutation.

Step 2-6: Testing the stop condition. Let f_s be the largest fitness among the population for the s^{th} evolution epoch. The stop condition is set based on whether the mature rate has reached a given constant η. If so, proceed to Step 3 and let s=$s+1$; otherwise go to Step 2-3.

Step 3: Testing the stop condition. If $(f_{s+1} - f_s) \leqq \varepsilon$, where ε is an arbitrary small number, then stop. Incumbent combination of logic rules and shapes of membership functions are the optimal learning results. Otherwise, go to Step 1.

In the first two categories, only one of the logic rule and membership function components is learned and the other component is set subjectively; thus, the applicability of that GFLC is very likely reduced. In the third category, both components are learned simultaneously, thus the efficiency and effectiveness of that GFLC could be declined due to a very long chromosome needed. In the fourth category, if both components are learned sequence, a time-consuming is for learning algorithm. In order to search optimal solution, the method should often have a strong assumption of membership functions (e.g. isosceles triangle). Thus, the outcome of GFLC could be produced the redundant and conflicting rules. To avoid these drawbacks, this research aim to develop a stepwise learning approach for logic rules and membership functions by using GAs.

2.3 Traffic Flow Simulator: Cell Transmission Model

In order to efficiently evaluate the performance of proposed traffic signal model in this research, the method and application of a macroscopic traffic flow theory, Cell Transmission Model (CTM), are briefly introduced below.

2.3.1 Basic theory of CTM

The CTM proposed by Daganzo (1994) can be used to predict traffic's evolution over time and space, including transient phenomena such as the building, propagation and dissipation of queues.

1. The theory of CTM

The CTM examines the evolution of traffic over a one-way road which has only an entrance and an exit, by updating current conditions with every tick of a clock. The road is divided equally into discrete 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 travelled by a vehicle in one clock tick under light traffic.

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

$$n_{i+1}(t+1) = n_i(t) \qquad \text{for } t = 0,1,2... \tag{2-17}$$

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 2 variables are introduced to incorporate queuing in the model:

$Q_i(t)$, 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

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

$$y_i(t) = \min\{n_{i\text{-}1}(t), Q_i(t), N_i(t) - n_i(t)\} \tag{2-18}$$

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:

$$n_i(t+1) = n_i(t) + y_i(t) - y_{i+1}(t) \tag{2-19}$$

Boundary conditions are specified for this model by input and output cells. The output cell, the "sink" for all exiting traffic, has infinite size ($N_{I+1} = \infty$) and a suitable time-varying capacity. A pair of cells are required for the input flow: the "source" cell numbered "00" has an infinite number of vehicles ($n_{00}(0) = \infty$) that discharges into the "gate" cell "0" of infinite size ($N_0(t) = \infty$). The latter has a function similar to an entrance ramp of a road, where in the case of a jam, vehicles will queue up on the ramp, unable to enter the road. The inflow capacity $Q_0(t)$ of the gate cell is set equal to the desired input flow for time interval $t + 1$.

2. Flow-density relationship of the CTM

The basic CTM assumes a homogenous system, where all cell characteristics are independent of i and t. It is shown to be a discrete approximation to the LWR model from its flow-density relationship, which is in the shape of an isosceles trapezoid (Figure 2.6). This relationship can be expressed as:

$$q = \min\{vk, q_{\max}, v(k_j - k)\} \qquad \text{for } 0 \le k \le k_j \tag{2-20}$$

where the maximum flow is $q_{max} \le k_j v/2$. Substituting Equation (2-20) into the flow conservation Equation ($\frac{\partial k}{\partial t} + \frac{\partial q}{\partial x} = 0$), the differential equation that would define the evolution of the system under the hydrodynamic model is obtained:

$$\frac{\partial \min\{vk(x,t), q_{\max}, v(k_j - k(x,t))\}}{\partial x} = -\frac{\partial k(x,t)}{\partial t} \tag{2-21}$$

The tick of the clock is defined as dt, and we set vdt, the unit of distance. Thus the cell length and v are 1, then

$$y = \min\{n_i(t), Q, N - n_i(t)\} \tag{2-22}$$

which coincides with the definition of y_{i+1} of Equation (2-18), except for the subindex of n, but as the system is homogenous, the number of cars in each cell is the same.

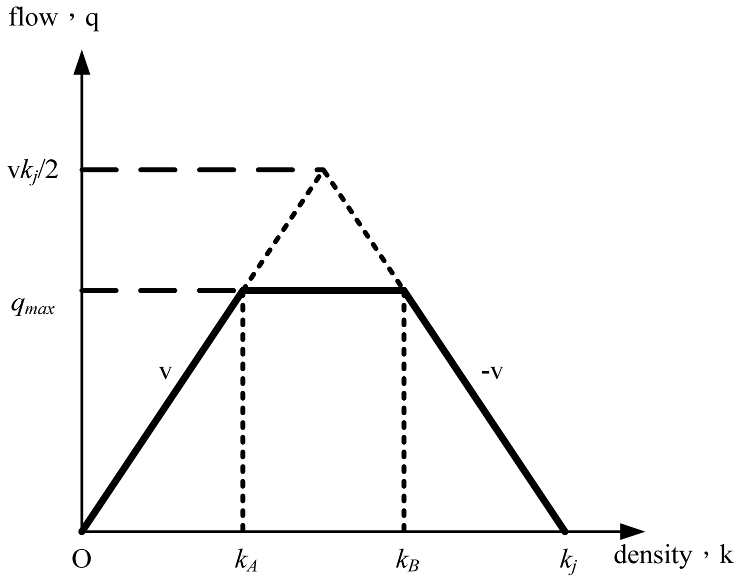


Figure 2.6 Flow-density relationship of the basic CTM.

In general, the continuous LWR model of Figure 2.7 can be solved by the Equations (2-19) and (2-20) when an infinitesimally small clock tick is used.

3. The Cell Transmission Model: General Case

The basic model had assumed that $w = v$. However, in reality, waves move several times slower than free flowing traffic, which was mentioned in (1). As $w < v$, queues persist for a longer time behind temporary bottlenecks and are dissipated further upstream. Thus, the basic CTM is modified for the general case to allow for $w \leq v$. Equations (2-19) and (2-20) are modified respectively:

$$q = \min\{vk, \mathrm{q}_{\max}, w(k_j - k)\} \qquad \text{for } 0 \leq k \leq k_j \tag{2-23}$$

where $w \leq v$ and $\mathrm{q}_{\max} \leq \dfrac{k_j}{\left[\dfrac{1}{v} + \dfrac{1}{w}\right]}$;

$$y_i(t) = \min\left\{n_{i-1}(t), Q_i(t), \frac{w}{v}[N_i(t) - n_i(t)]\right\} \tag{2-24}$$

The differential equation defining the system evolution under the LWR model on a homogeneous system, formerly Equation (2-21), becomes:

$$\frac{\partial \min\{vk(x,t), \mathrm{q}_{\max}, w(k_j - k(x,t))\}}{\partial x} = -\frac{\partial k(x,t)}{\partial t} \tag{2-25}$$

Finally, compare the two *q*-*k* diagrams in Figure 2.7 and observe that the *q*-*k* diagram of the generalized CTM (left) is similar to the Fundamental Diagram of traffic flow (right) derived from LWR model.

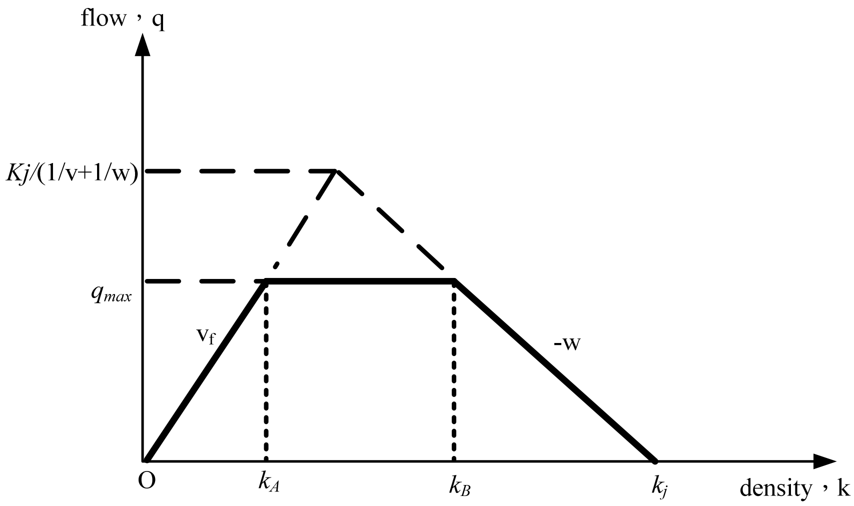


Figure 2.7 Flow-density diagrams obtained from the CTM and LWR model.

2.3.2 Mixed traffic cell-transmission model (MCTM)

This study aims to develop an adaptive urban traffic signal controller. The traffic component of urban road includes passenger cars and motorcycles in Asian area. In order to accurately simulate traffic, this subsection reviews some mixed traffic flow models and mixed traffic cell-transmission model proposed by Chiou and Hsieh (2011).

To facilitate the learning process of the proposed SGFLC model, an efficient traffic simulator is imperial to evaluate the performance of selected logic rules and tuned membership functions in a short period. Based on this, a cell-based traffic simulator, CTM, is considered. CTM, proposed by Daganzo (1994; 1995) for simulating traffic hydrodynamic behavior, uses several simple equations to govern traffic movements along the roadway which is represented by a series of equal-length cells. These equations are expressed as follows:

$$n_i(t+1) = n_i(t) + y_i(t) - y_{i+1}(t) \tag{2-26}$$

$$y_i(t) = \min\{n_{i-1}(t), q_{mi}(t), \beta[N_i(t) - n_i(t)]\} \tag{2-27}$$

$$\beta = \begin{cases} 1, \text{if } n_{i-1}(t) \le q_{mi}(t) \\ \dfrac{w}{v}, \text{if } n_{i-1}(t) \ge q_{mi}(t) \end{cases} \tag{2-28}$$

Based on the pure traffic CTM, Chiou and Hsieh (2011) developed and validated a mixed traffic CTM (MCTM) for the traffic flow of cars and motorcycles. In Chiou and Hsieh's model, the variable $n_i(t)$ is decomposed into $n_i^c(t)$ and $n_i^m(t)$ for representing the numbers of cars and motorcycles in cell *i* at time *t*, respectively. Thus, Eq. (2-26) can be revised as:

$$\begin{aligned} n_i^c(t+1) &= n_i^c(t) + y_i^c(t) - y_{i+1}^c(t) \\ n_i^m(t+1) &= n_i^m(t) + y_i^m(t) - y_{i+1}^m(t) \end{aligned} \tag{2-29}$$

Both types of vehicles exhibit rather different traffic behaviors in competing roadway capacity and remaining storage space. Thus, the parameters of the MCTM, including maximal flow rate, maximal storage capacity, and remaining storage capacity, should be dynamically adjusted and allocated between cars and motorcycles according to mixture ratio of vehicles types. Depending upon various traffic conditions, three situations are detailed below:

1. Free flow condition: No competition between cars and motorcycles

The flow and density of cars and motorcycles, in upstream cell, are less than maximal flow and remaining capacity of downstream cell. This condition refers to the first condition of Eq.(2-27) which the vehicles can transmit from upstream to downstream without any deter.

2. Maximal flow competition between cars and motorcycles

This situation occurs when numbers of cars and motorcycles in upstream cell exceed maximal flow (i.e. the second condition of Eq.(2-27)). Thus, cars and motorcycles compete to transmit from upstream cell to downstream cell. This competition behavior can be elaborated as follows:

$$Q_i^m(t) = \frac{[R_m^Q(n_{i-1}^c(t), n_{i-1}^m(t)) \times q_{mi}(t)]}{\alpha}$$
$$Q_i^c(t) = [1 - R_m^Q(n_{i-1}^c(t), n_{i-1}^m(t))] \times q_{mi}(t) \tag{2-30}$$

where flow competition functions, $R^Q(n_{i-1}^c(t), n_{i-1}^m(t))$, is a function of the numbers of cars and motorcycles.

According to field observations, the interferences between cars and motorcycles are rapidly increased as the mixture ratio of cars and motorcycles becomes higher. Thus, Chiou and Hsieh (2011) introduced the entropy concept to dynamically adjust PCE by defining the competition relationship as:

$$R_m^Q(n_{i-1}^c(t), n_{i-1}^m(t)) = \frac{\eta \times n_{i-1}^m(t)}{\eta \times n_{i-1}^m(t) + n_{i-1}^c(t)} \tag{2-31}$$

where η is the adjusted PCE of motorcycles, which is assumed to linearly increase as the entropy can become higher from a base value of PCE (α):

$$\eta = \alpha + (\varepsilon \times H(n_{i-1}(t))) \tag{2-32}$$

where $H(n_{i-1}(t))$ is an entropy function measuring by the proportions of cars (p^c) and motorcycles (p^m):

$$H(n_{i-1}(t)) = -[p^m(n_{i-1}(t)) \log p^m(n_{i-1}(t)) + p^c(n_{i-1}(t)) \log p^c(n_{i-1}(t))] \tag{2-33}$$

The proportions of cars (p^c) and motorcycles (p^m) in upstream cell can be calculated by Eqs. (2-37) and (2-35), respectively:

$$p^c(n_{i-1}(t)) = \frac{l \times n_{i-1}^c(t)}{n_{i-1}^m(t) + l \times n_{i-1}^c(t)} \tag{2-34}$$

$$p^m(n_{i-1}(t)) = \frac{n_{i-1}^m(t)}{n_{i-1}^m(t) + l \times n_{i-1}^c(t)} \tag{2-35}$$

where, l=space of a car /space of a motorcycle.

3. Remaining storage capacity competition between cars and motorcycles

This competition behavior occurs when remaining storage capacity in the downstream cell can not accommodate all vehicles transmitting from the upstream cell (i.e. $l \times n_{i-1}^c(t) + n_{i-1}^m \geq S_i(t)$). In addition, the motorcycles can still "sneak" into the downstream cell when remaining storage capacity can not accommodate a car. In order to reflect this phenomenon, a congestion index (δ) is introduced to determine how the remaining storage space ($S_i(t)$) is allocated:

$$S_i(t) = \delta \times \{N_i(t) - [l \times n_i^c(t) + n_i^m(t)]\} \tag{2-36}$$

where $\delta = \begin{cases} 1 & \text{if } n_{i-1}^c(t) + \alpha \times n_{i-1}^m(t) \leq q_{mi}(t) \\ \dfrac{w}{v} & \text{if } n_{i-1}^c(t) + \alpha \times n_{i-1}^m(t) > q_{mi}(t) \end{cases}$

Consider a space competition function, $R_m^S(n_{i-1}^c(t), n_{i-1}^m(t))$ which allocates remaining storage space between cars and motorcycles moving from upstream to downstream. The remaining storage capacity is then allocated to cars ($S_i^c(t)$) and motorcycles ($S_i^m(t)$) is expressed as:

$$S_i^c(t) = R_m^S(n_{i-1}^c(t), n_{i-1}^m(t)) \times S_i(t) \tag{2-37}$$

$$S_i^m(t) = \frac{[1 - R_m^S(n_{i-1}^c(t), n_{i-1}^m(t))] \times S_i(t)}{l} \tag{2-38}$$

Logghe and Immers (2008) indicated that the higher density of vehicles of class i on road has advantage to move forward. Thus, the competition functions can be expressed as:

$$R_m^S(n_{i-1}^c(t), n_{i-1}^m(t)) = \frac{n_{i-1}^m(t)}{n_{i-1}^m + l \times n_{i-1}^c(t)} \tag{2-39}$$

In sum, based on the pure traffic CTM proposed by Daganzo in Eqs. (2-19) and (2-20), the mixed traffic CTM with cars and motorcycles proposed by Chiou and Hsieh (2011) can replicate mixed traffic by Eqs. (2-40) and (2-41).

$$\begin{aligned} n_i^c(t+1) &= n_i^c(t) + y_i^c(t) - y_{i+1}^c(t) \\ n_i^m(t+1) &= n_i^m(t) + y_i^m(t) - y_{i+1}^m(t) \end{aligned} \tag{2-40}$$

$$\begin{aligned} y_i^c(t) &= \min\{n_{i-1}^c(t), [1 - R_m^Q(n_{i-1}^c(t), n_{i-1}^m(t))] \times q_{mi}(t), \frac{[1 - R_m^S(n_{i-1}^c(t), n_{i-1}^m(t))] \times S_i(t)}{l}\} \\ y_i^m(t) &= \min\{n_{i-1}^m(t), \frac{[R_m^Q(n_{i-1}^c(t), n_{i-1}^m(t)) \times q_{mi}(t)]}{\alpha}, R_m^S(n_{i-1}^c(t), n_{i-1}^m(t)) \times S_i(t)\} \end{aligned} \tag{2-41}$$

2.3.3 Applications of CTM

The macrocsopic traffic flow theory cell-transmission model (CTM) proposed by Daganzo (1994) and Lebacque (1996), to the kinematic wave partial differential equation of Lighthill and Whitham (1955) and Richards (1956).

The popularity of CTM is due to its very low computation requirements compared with micro-simulation models; the ease with which it can be calibrated using routinely available point detector data (Lin and Ahanotu, 1995; Munoz et al., 2004); its extensibility to networks (Waller and Ziliaskopoulos, 2001) and urban roads with signalized intersections (Lo, 2001; Almasri and Friedrich, 2005); and the flexibility with which it can be used to pose questions of traffic assignment (Lo and Szeto, 2002; Ziliaskopoulos, 2000) and ramp metering (Daganzo and Lin, 1993; Zhang et al., 1996; Gomes and Horowitz, 2006). Despite their simplicity, field data suggested that they fit measurements well. See for example, Lin and Ahanotu (1995) and Smilowitz and Daganzo (1999). These two studies validated CTM for freeway and arterial traffic. According to the descriptions above, CTM is a widely used discrete macroscopic model and can simulate as well as plausible model for signalized urban streets.

2.4 Summary

On-line traffic signal control can provide signal-timing plans in response to real-time traffic conditions. The well-known adaptive signal controllers mentioned above employ mathematical equations or models to determine “crisp” threshold values as the cores of control mechanism; thus, the control performance could be negatively affected by the uncertainty of traffic conditions. Since a fuzzy control system has excellent performance in data mapping as well as in treating ambiguous or vague judgment. In classical FLC systems however, methods for formulating the rule base and data base are subjectively preset, not optimally solved. Employing GAs to construct an FLC system with learning process from examples can not only avoid the bias caused by subjective settings of logic rules or membership functions but also greatly enhance the control performance. On the other hand, how to evaluate the performance of signal control models is an important issue. To facilitate the learning process of the GFLC, an efficient traffic simulator is necessary to evaluate the performance of a set of selected logic rules and tuned membership functions in a very short period. CTM, proposed by Daganzo (1994, 1995) to simulate traffic hydrodynamic behavior in a macroscopic manner, uses several simple equations to govern traffic movements along the roadway which is represented by a series of equal-length cells. Based on the pure traffic CTM, Chiou and Hsieh (2011) developed and validated a mixed traffic CTM (MCTM) for the traffic flow of cars and motorcycles. Besides, the mixed traffic should be considered when determined the urban traffic signal control timing plan. The details of these proposed models or concepts are described in the following chapter.

Chapter 3 METHODOLOGIES

The model framework is shown in Figure 3.1. This study aims to develop an adaptive traffic signal controller for isolated intersection, sequential intersections and a long corridor. Thus, signal control logic both for isolated intersection and sequential intersection, including arterial approach and competing approaches, should be presented. On the other hand, the method integrating GA into the FLC with stepwise algorithm are developed. Combination with GA-based clustering algorithm, the proposed SGFLC model is able to not only conduct adaptive signal control but also to determine which intersections have to be coordinated with.

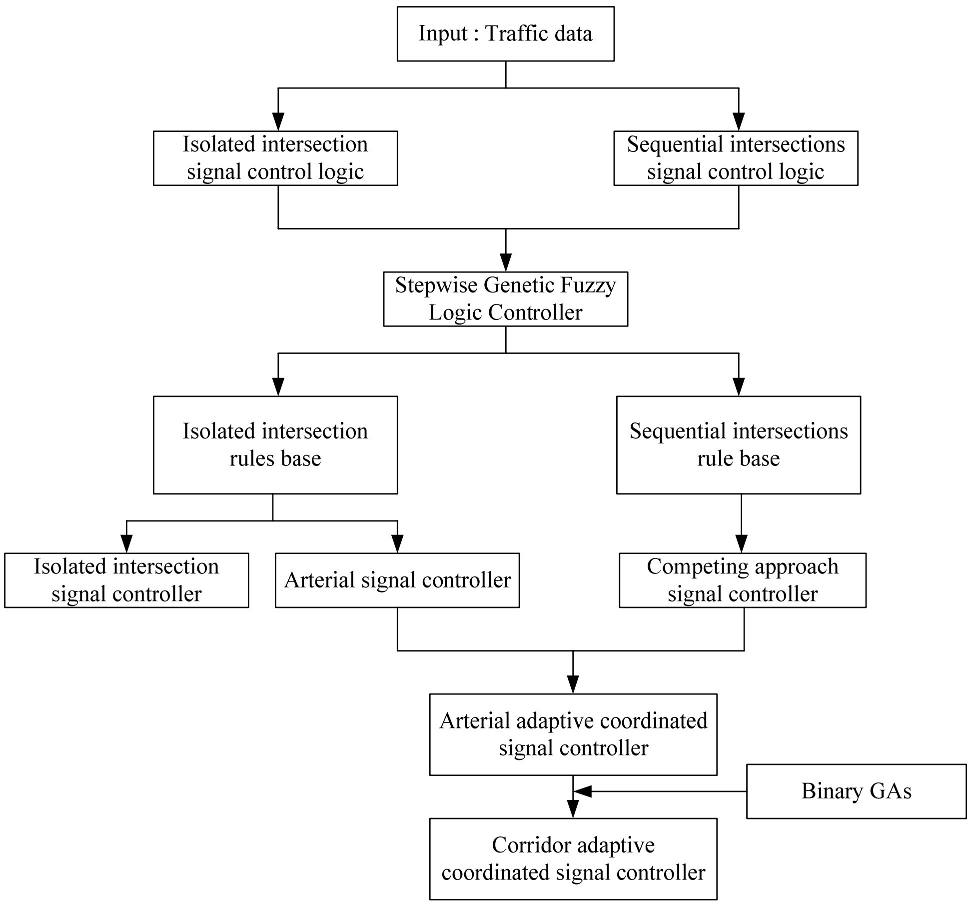


Figure 3.1 SGFLC model framework.

This chapter first introduced the concept of the FLC-based traffic signal control model and the design of the FLC. Then the design stepwise evolution algorithm with GA of the FLC is presented. In the last sections of this chapter, introduce the binary genetic algorithm to cluster the coordinate intersections along a long corridor.

3.1 Traffic Signal Control Logic

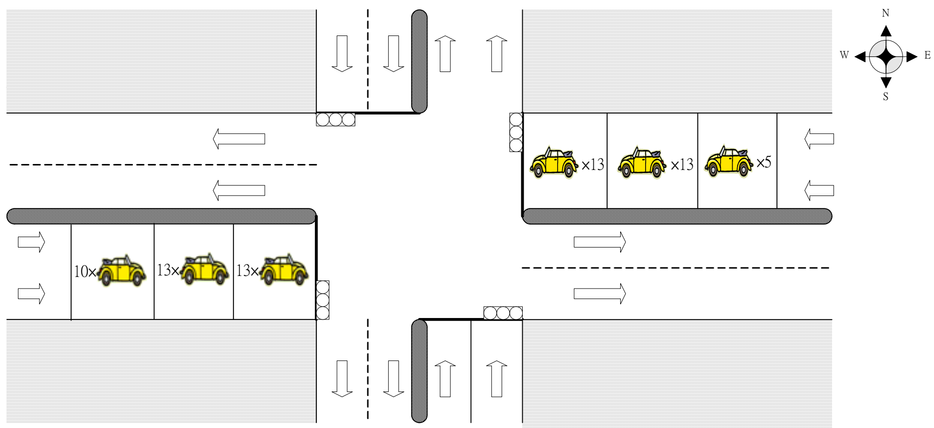
3.1.1 Fitness value

The performances of signal control for an isolated intersection or sequential intersections are commonly measured in terms of total number of stopped vehicles, proportion of stopped vehicles, average vehicle delays, total vehicle delays, maximal green band, etc. This study sets the total vehicle delays (*TVD*) as the control performance index and thus defines the fitness function of GAs as:

$$f = \frac{1}{TVD} \tag{3-1}$$

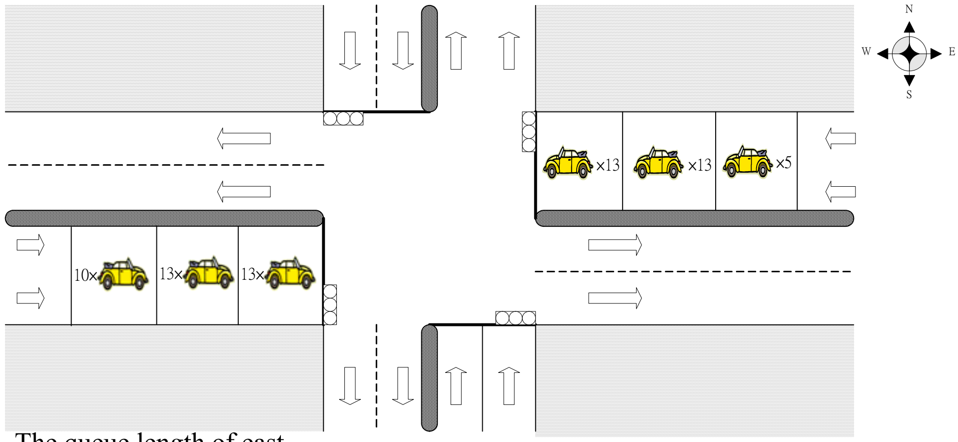
3.1.2 State and control variables

Following most of the previous literature, for the case of an isolated intersection, we choose traffic flow in green phase (*TF*) and queue length in red phase (*QL*) as two state variables and extension of green time (*EGT*) as the control variable. For the case of sequential intersections, *TF* is the summation of traffic flows at all approaches in green phase; while *QL* is the summation of queen length at all approaches in red phase. Figure 3.2 shows the calculation method for both *QL* and *TVD*. Beside, the more traffic flow arrival rate may cause longer queue length in the same direction. Thus, the relationship between those two state variables may be positive.



(a) Calculation for state variable *QL*

Assume east and west bound is red phase north and south is green phase.
The parameters of CTM : N=13, tick of clock=2sec



The queue length of east-west bound (QL_{ew}) is 36
The delay of east-west bound= 36×2=72

The queue length of west-east bound (QL_{we}) is 31
The delay of west-east bound= 31×2=62

The TVD of this time period is 62+72=134

(b) Calculation for fitness value *TVD*

Figure 3.2 Calculation methods for *QL* and *TVD*.

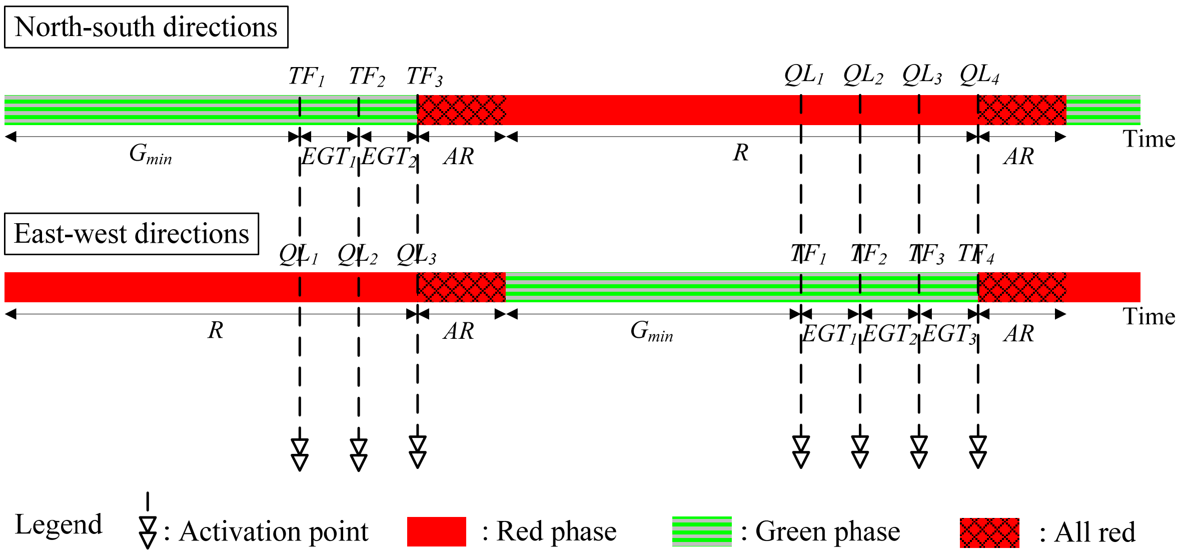
To reflect the different details of mixed traffic flow, three dimensions with different considerations of state variables are developed. Dimension 1 considers four state variables: traffic flow of cars (*TFC*), traffic flow of motorcycles (*TFM*), queue length of cars (*QLC*) and queue length of motorcycles (*QLM*). Dimension 2 considers two state variables by weighted summing up cars and motorcycle traffic: traffic flow *TFP* ($TFP = TFC + \alpha TFM$) and queue length *QLP* ($QLP = QLC + \alpha QLM$), where α is the PCE of motorcycles (0.3 in this study). Dimension 3 also considers two state variables by simply summing up car and motorcycle traffic: traffic flow *TFV* ($TFV = TFC + TFM$) and queue length *QLV* ($QLV = QLC + QLM$).

3.1.3 Activation points

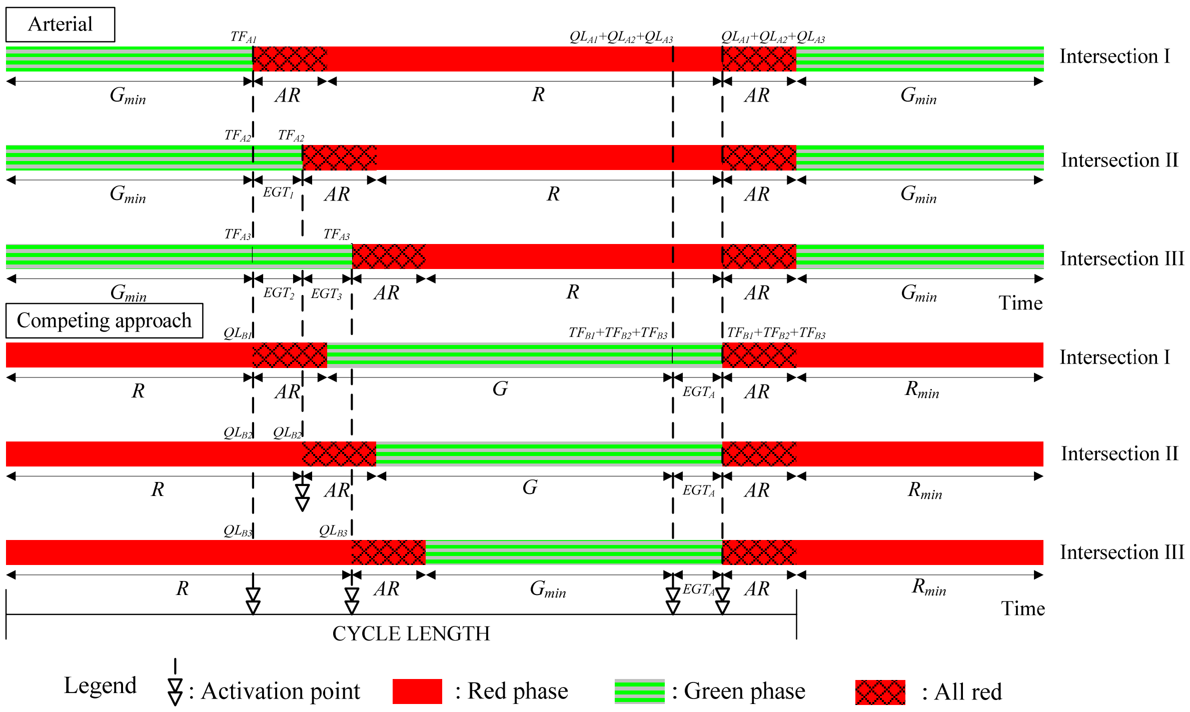
In consideration of pedestrian safe crossing, a minimum green time (G_{min}) in each green phase is preset both for an isolated intersection or sequential intersections. At the end of G_{min}, the proposed stepwise GFLC model is activated automatically to conclude an *EGT*. If $EGT \geq EGT_{min}$ (a preset value), current green phase is extended by *EGT* seconds. If $EGT < EGT_{min}$, current green phase is then terminated. The SGFLC model will not be activated again until the end of this extension time. If total green time exceeds the preset maximum green time (G_{max}), current green phase is forced to terminate. A short all-red (*AR*) period is designed in each signal change interval. The activation points for an isolated intersection are also depicted in

Figure 3.3(a).

This study also uses of the SGFLC model to adaptively control the signals of sequential intersections along an arterial. To reflect the various traffic conditions of different coordinated intersections, the green times along the arterial are independently determined by following the same control mechanism of an isolated intersection. However, to synchronize the signal timing plans of all coordinated intersections, an integrated signal control mechanism by considering the summation of traffic flows at all approaches in green phase and summation of queen length at all approaches in red phase. Therefore, the cycle length of all coordinated intersections is kept the same. It should be noted that the activation of extended red time of the arterial (i.e. the extended green time of competing approaches) won't be started until all intersections along the arterial have been turned into red phase. Figure 3.3(b) illustrates the activation points and signal timings for one of the sequential intersections.



(a) Isolated intersection



(b) Sequential intersections

Figure 3.3 Activation points for an isolated intersection and sequential intersections.

3.2 Stepwise GFLC Model (SGFLC)

Since the IGFLC has to learn logic rules and membership functions iteratively, making the learning process rather time-consuming. In order to search near optimal solution, the method should often have a strong assumption of membership functions (e.g. isosceles triangle). Thus, the outcome of GFLC could be produced the redundant and conflicting rules. To avoid these drawbacks, this research develops a stepwise learning approach for logic rules and membership functions by using GAs.

The proposed SGFLC model has three key parts, including encoding methods, genetic operators and stepwise evolution algorithm, which are explained in more details bellow.

3.2.1 Encoding logic rules and membership functions

Consider a triangle fuzzy number and let parameters c^r, c^c and c^l respectively represent the coordinates of right anchor, cortex and left anchor of a linguistic degree as shown in Figure3.2 Therefore, a variable with a linguistic degree has 3 parameters need to be calibrated and their orders are:

$$c^r \leq c^c \leq c^l \tag{3-2}$$

Thus, if we employ GAs to tune the aforementioned parameters directly, the search performance will deteriorate significantly as a result of incorporating all the constraints. To overcome this problem, the encoding method proposed by Chiou and Lan (2005) is employed. In order to tune these 3 parameters, 3 position variables $r_1 \sim r_3$ are designed as follows:

$$c^l = r_1 \tag{3-3}$$

$$c^c = r_1 + r_2 \tag{3-4}$$

$$c^r = r_1 + r_2 + r_3 \tag{3-5}$$

To achieve two significant digits, each position variable is represented by four real-coding genes also depicted in Figure 3.4 The maximum value of the position variables is 99.99 and the minimum value is 0. Thus, in the example of two state variables and one control variable, the chromosome is composed of 36 genes.

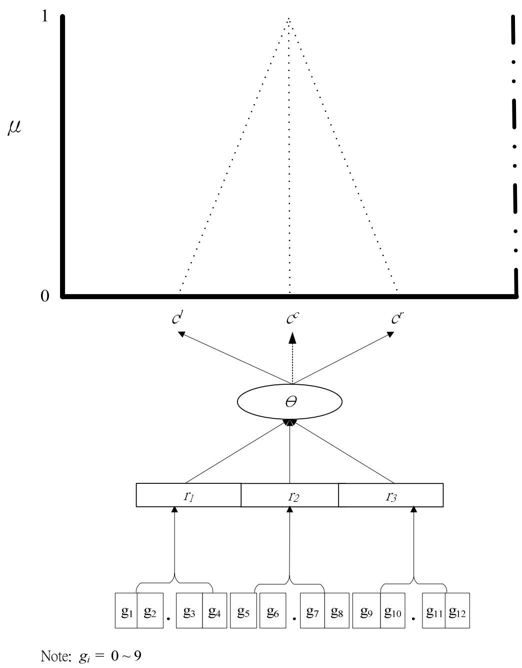


Figure 3.4 Encoding method for logic ruses and membership functions.

3.2.2 Genetic operators

The max-min-arithmetical crossover proposed by Herrera *et al.* (1995) and the non-uniform mutation proposed by Michalewicz (1992) are employed. In the max-min-arithmetical crossover, let $G_w^t = \{ g_{w1}^t, \ldots, g_{wk}^t, \ldots, g_{wK}^t \}$ and $G_v^t = \{ g_{v1}^t, \ldots, g_{vk}^t, \ldots, g_{vK}^t \}$ be two chromosomes selected for crossover, the following four offsprings will be generated (Herrera *et al.*,1995):

$$G_1^{t+1} = aG_w^t + (1\text{-}a)G_v^t \tag{3-6}$$
$$G_2^{t+1} = aG_v^t + (1\text{-}a)G_w \tag{3-7}$$
$$G_3^{t+1} \text{ with } g_{3k}^{t+1} = min\{g_{wk}^t, g_{vk}^t\} \tag{3-8}$$
$$G_4^{t+1} \text{ with } g_{4k}^{t+1} = max\{g_{wk}^t, g_{vk}^t\} \tag{3-9}$$

where a is a parameter ($0 < a < 1$) and t is the number of generations. In the non-uniform mutation, let $G_t = \{ g_1^t, \ldots, g_k^t, \ldots, g_K^t \}$ be a chromosome and the gene g_k^t be selected for mutation (the domain of g_k^t is $[g_k^l, g_k^u]$), the value of g_k^{t+1} after mutation can be computed as follows:

$$g_k^{t+1} = \begin{cases} g_k^{\ t} + \Delta(t, g_k^u - g_k^{\ t}) & if \quad b = 0 \\ g_k^{\ t} - \Delta(t, g_k^{\ t} - g_k^l) & if \quad b = 1 \end{cases} \tag{3-10}$$

where b randomly takes a binary value of 0 or 1. The function $\Delta(t,z)$ returns a value in the range of [0, z] such that the probability of $\Delta(t,z)$ approaches to 0 as t increases:

$$\Delta(t,z) = z(1 - r^{(1-t/T)^h}) \tag{3-11}$$

where r is a random number in the interval [0,1], T is the maximum number of generations and h is a given constant. In Equation (3-11), the value returned by $\Delta(t,z)$ will gradually decrease as the evolution progresses.

3.2.3 Learning algorithm

The stepwise algorithm for selecting the logic rules with the membership functions is similar to a stepwise process in data mining. At each stage in process, after a new rule is added, a test is made to check if one rule can be deleted without appreciably improve the objective value. The procedure will not terminate until the fitness value improvement falls below some critical value. Consider an FLC with n state variables x_1, x_2 ,…, x_n and one control variable y. The stepwise learning algorithm is structured as follows:

Step 0: Initialization: $s=1$.

Step 1: Renew the storage of logic rules.

Step 2: Tuning membership functions.

Step 2-1: Generating an initial population with p chromosomes. Each chromosome has $12(n+1)$ genes and each gene randomly takes one integer from $[0, 9]$.

Step 2-2: Calculating the fitness values of all chromosomes based on the incumbent combination with storage of logic rules.

Step 2-3: Selection.

Step 2-4: Crossover.

Step 2-5: Mutation.

Step 2-6: Testing the stop condition. Let f_s be the largest fitness among the population for the s^{th} evolution epoch. The stop condition is set based on whether the mature rate has reached a given constant η. If so, proceed to Step 3 and let $s=s+1$; otherwise go to Step 2-3.

Step 3: Testing the stop condition. If $(f_{s+1} - f_s) \leqq \varepsilon$, where ε is an arbitrary small number, then stop and renew the storage of logic rules. Incumbent combination of the storage of logic rules are the near optimal learning results. Otherwise, go to Step 1. The evaluation process of SGFLC was shown in Figure 3.5.

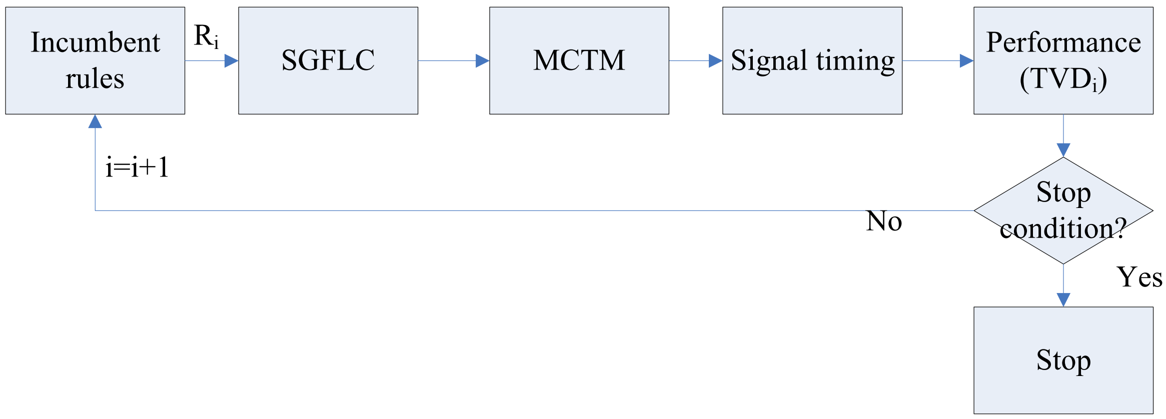


Figure 3.5 The evaluation process of SGFLC.

3.3. Determining the Coordinated Intersections

It is well-known that the control performance of signal coordination would be greatly degraded as the number of coordinated intersections increases. Therefore, this study introduces a binary genetic algorithm to determine which intersections to be coordinated and how many clusters of coordinated intersections would be.

3.3.1 Typical operation of binary GA cluster

In each generation, the selection is a process by which the chromosomes, coded strings, with larger fitness values can produce accordingly with higher probabilities large number of their copies in the new generation. The crossover is a process by which the systematic information exchange between two coded strings is implemented using probabilistic decisions. In a crossover process, two coded strings are chosen from the matching pool and arranged to exchange their corresponding positions of binary strings at a randomly selected partitioning position along them. This process can combine better qualities among the preferred good strings. And then the mutation is a process by which the chance for the GA to reach the near optimal point is reinforced through just an occasional alteration of a value at a randomly selected bit position. The mutation process may quickly generate those strings which might not be conveniently produced by the previous selection and crossover process to avoid the trap of local solutions. The GA runs iteratively repeating the above process until it arrives at a predetermined ending condition. The process of going from the current population to the next population constitutes one generation in the execution of a GA. A typical GA cycle is depicted as Figure 3.6.

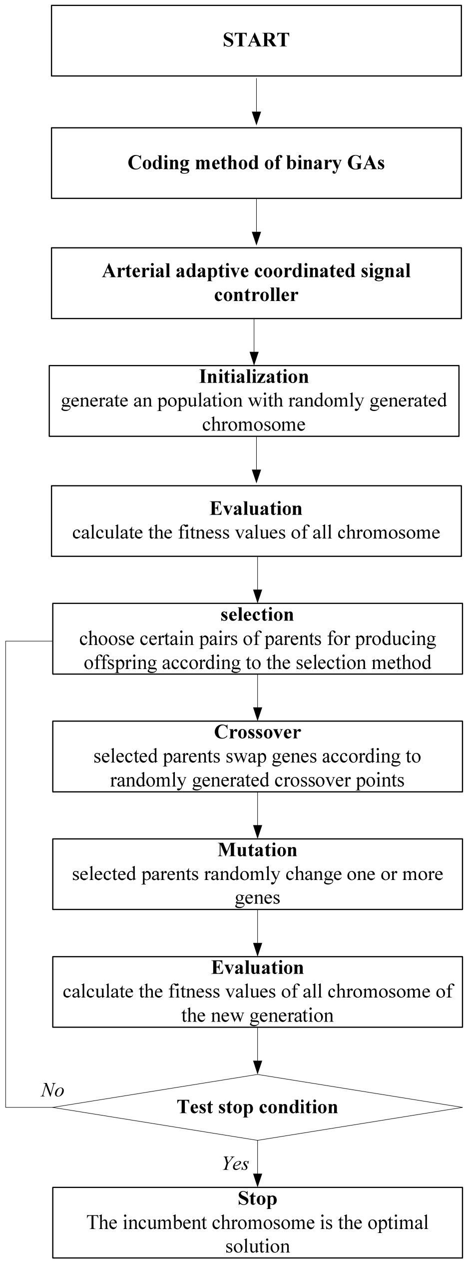


Figure 3.6 Typical operation of binary GA.

3.3.2 Coding method

This study adopts binary coding method to represent the intersection is coordinated with the very next (downstream) intersection or not. Each intersection is represented by one gene. The neighboring intersections sharing the same gene value are in the same coordination plan. Taking a corridor with 10 intersections as an example, the chromosome taking values of 0011101000 represents five clusters of signal coordination plans being formed, which suggests that intersections 1 and 2 are coordinated as Cluster1; intersections 3, 4, 5 are coordinated as Cluster 2: intersections 6 and 7 are self-clustered and independently operated denoted as Cluster 3 and Cluster 4, respectively. Intersections 8, 9 and 10 are then coordinated as Cluster 5.

3.3.3 Fitness value

The performances of a long corridor are commonly measured in terms of total number of stopped vehicles, proportion of stopped vehicles, average vehicle delays, total vehicle delays, maximal green band, etc. This study chooses the total vehicle throughput (*TVT*) including main arterial and competing approaches as the control performance index and thus defines the fitness function of GAs as:

$$f = TVT \tag{3-12}$$

Chapter 4 ISOLATED INTERSECTION

To investigate the effectiveness and robustness of the proposed signal control model, comparisons to two pre-timed models and three adaptive models are conducted at an experimental isolated intersection. Beside, the validation of MCTM is described at the beginning of Chapter 4.

4.1 Validation of MCTM

To validate the MCTM in replicating the traffic behaviors at signalized intersections in Taiwan, field traffic data were collected at one of approaches of a signalized intersection in Taipei on February 27, 2009. The study approach was divided into six cells depending on free flow speed and length of time step, as shown in Figure 4.1. The traffic moves from cell 1 to cell 6 and y_I and y_O denotes the traffic flows in and out the study approach. The stop line of the intersection locates at the right bound of cell 6. The performance of the MCTM is shown in Table 4.1. As noted from Table 4.1, the MAPE values are less than 30% in most of cells in both green and red time. In addition, the simulation results are more accurate at the cells closer to the stop line and for motorcycle traffic.

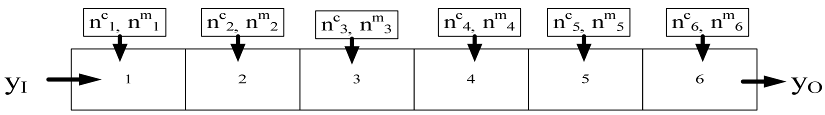
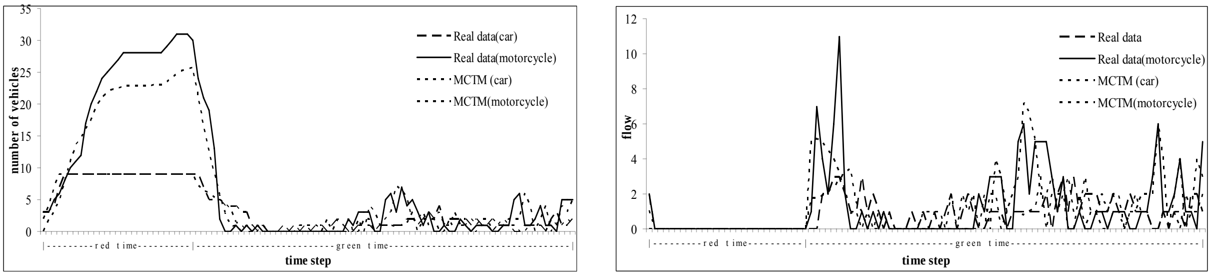


Figure 4.1 Configuration of the validated approach.

Table 4.1 Validation results of the mixed CTM in different cells and phases.

Phase	Performance	Vehicle types	Cell 1	2	3	4	5	6	y_{6I}
Green (120 seconds)	MAPE	car	26.71%	42.80%	34.46%	10.90%	16.81%	15.79%	8.05%
		motorcycle	23.60%	38.95%	30.63%	3.38%	8.17%	11.75%	3.48%
	RMSE	car	17.70	20.75	19.01	10.17	13.17	21.09	5.16
		motorcycle	24.85	32.56	26.06	4.50	11.29	25.59	6.05
Red (50 seconds)	MAPE	car	30.42%	11.42%	24.60%	28.24%	27.66%	11.49%	-
		motorcycle	6.21%	26.89%	27.40%	21.19%	33.31%	16.21%	-
	RMSE	car	2.03	0.71	3.18	22.06	32.33	31.56	-
		motorcycle	1.12	3.30	3.84	6.98	13.96	91.87	-

According to the number of vehicles and flow at cell 6 in red time and green time, this study also validates the queuing behavior in red phase and platoon dispersion in green phase. The results are shown in Figure 4.2(a) and (b) respectively. The results show that the CTM can satisfactorily replicate the traffic behaviors at the signalized intersection.



(a)Number of vehicles (b)Flow

Figure 4.2 Number of vehicles and flow at cell 6 in red time and green time.

4.2 Parameter Setting and Traffic Data

To validate the effectiveness and robustness of the proposed SGFLC signal control model, an experimental example for an isolated four-leg intersection (Figure 4.3) is demonstrated. The percentages of turning flow are setting as: left turning (P_{LT})=0.2, right turning (P_{RT})=0.2. The parameters of the MCTM are set as: free-flow speed=50km/h, time step=2 seconds, k_j=130 veh/km/lane. Assume that the intersection has two lanes ($N_i(t)$=3.6 cars/cell for all i and t) in each approach with saturation flow of 1800 pcu/hr/lane ($q_{mi}(t)$=2.00 veh/time step for all i and t). The flow patterns of five-minute flow rates in different approaches are given in Figure 4.4. A noticeable peak and off-peak traffic patterns are assumed in east and west directions; while rather flat traffic patterns are assumed in north and south directions. The parameters of the SGFLC model are set as population size=100, crossover rate=0.9, a=0.3, h=0.5, η=80%, ε=0.05. The center of gravity method is employed for defuzzification. The parameters of signal control are: G_{max}=100 seconds, G_{min}=20 seconds, all red + lost time =6 seconds, EGT_{max}=20 seconds, and EGT_{min}=4 seconds.

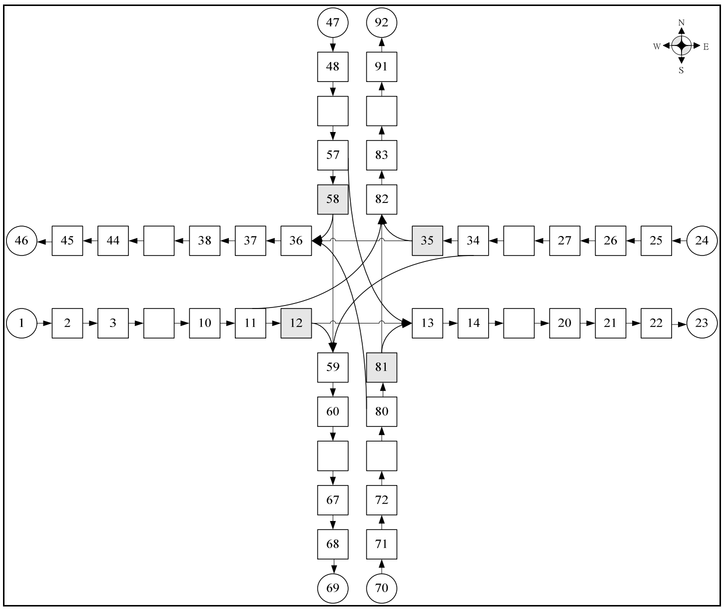
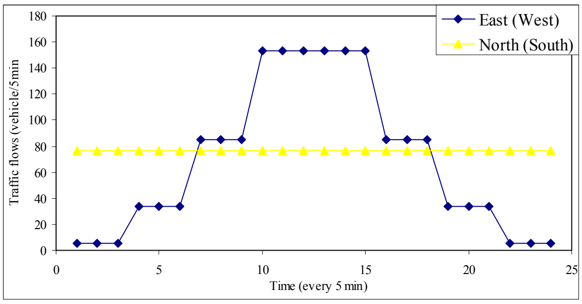
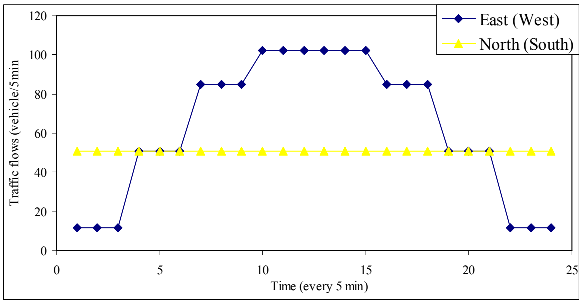


Figure 4.3 Configuration of the experimental isolated intersection.



(a) car flow rates



(b) motorcycle flow rates

Figure 4.4 Five-minute flow rates at the experimental isolated intersection.

4.3 Model Training and Performance

The training results of the stepwise GFLC signal control model for various mutation rates are reported in Table 4.2. As shown in Table 4.2, the SGFLC performs best at the mutation rate of 0.05 with corresponding *TVD* of 58.34. The values of *TVD* achieved by the SGFLC model under various mutation rates do not significantly differ, but the number of generations progressed tends to rapidly grow as the mutation rate increases.

Table 4.2 The results of SGFLC with various mutation rates (*Pm*).

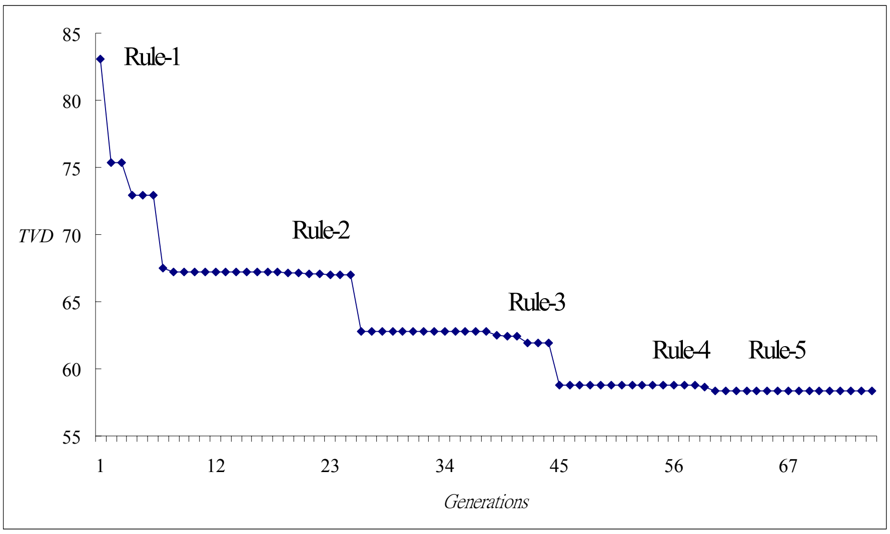
Pm	0.01	0.03	0.05	0.07	0.10	0.20	0.30	0.40	0.50
No. of generations	149	111	75	204	125	234	168	676	853
TVD	59.40	58.92	58.34	59.69	62.00	62.09	60.65	59.16	58.68

Furthermore, Table 4.3 compares the control performances of three different details of traffic measurements of SGFLC models. As shown in Table 4.3, Dimension 1 performs best with lowest *TVD* of 58.34 vehicle-hour, suggesting the more details in traffic measurement the better performance can be achieved. In what follows, only the learning results and control performance of dimension 1 is further elaborated and compared.

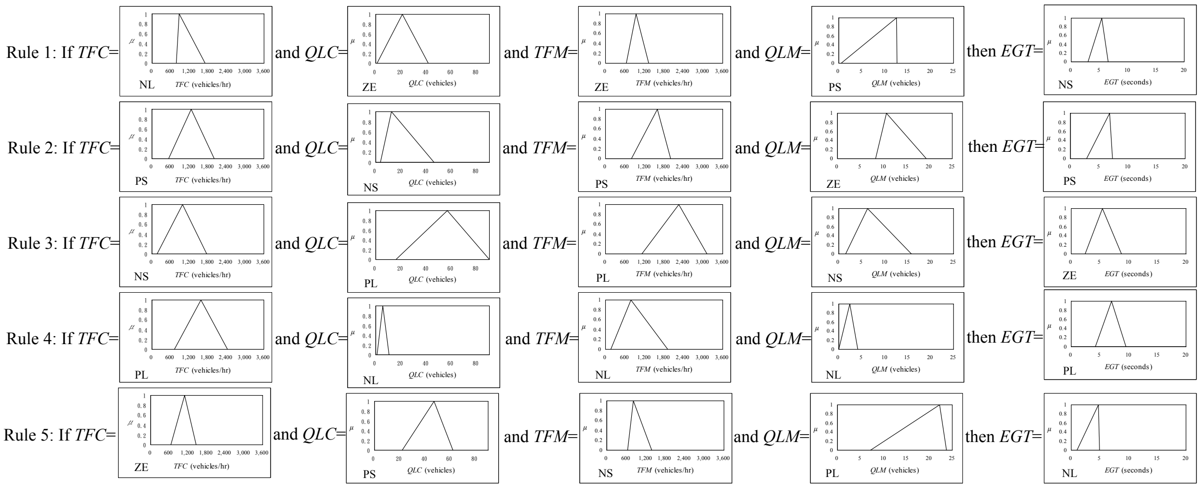
Table 4.3 Control performances of the SGFLC models with various state variables.

Dimensions	State variables	Generations	*TVD*	Number of selected rules
Dimension 1	*TFC,TFM,QLC* and *QLM*	75	58.34	5
Dimension 2	*TFP* and *QLP*	95	65.03	8
Dimension 3	*TFV* and *QLV*	113	65.19	7

The learning process of the Dimension 1 is depicted in Figure 4.5(a). Note that SGFLC converges after five stepwise evolutions with a total of 75 generations progressed. The value of *TVD* decreases from 83.09 to 58.34 veh-hour. A total of five rules are selected after five stepwise evolutions. Figure 4.5(b) presents the near optimally selected five logic rules along with corresponding tuned membership functions.



(a) Learning process



(b) Selected logic rules and tuned membership functions

Figure 4.5 Learning process and results of the SGFLC model at the isolated intersection.

4.4 Model Validation and Comparisons

To validate the effectiveness, the control performance of the SGFLC model is compared with two pre-timed models: optimal single (OS) and optimal multiple (OM) and three adaptive models: iterative genetic fuzzy logic control (IGFLC) model, vanishing queue (VQ) and maximum queue (MQ). Where the OS timing plan is determined by total enumeration method to search for an optimal cycle length and green time during the study period. The OM timing plan comprises seven optimal single timing plans depends on traffic flow pattern as shown in Figure 4.2 Since the OM model designs the optimal signal timings for each of traffic flow rates, its control performance is optimal for the given traffic pattern. The IGFLC model proposed by Chiou and Lan (2005) is to simultaneously and iteratively select all combination rules and then tune all membership functions of linguistic variables. The VQ model proposed by Lin and Lo (2008) is an actuated control system by switching traffic signal to serve the other approach whenever the queue on the current approach vanishes; while the MQ model switches traffic signal to serve the other approach when the queue length on the that approach reaches a preset maximum queue. In this study, the maximum queue length is optimized via a try-and-error manner.

Table 4.4 summarizes the comparison results. Comparing to the OS model, the proposed SGFLC model can curtail 6.47 vehicle-hours (11.09%) and incur only 0.60 more vehicle-hours (1.03%) delays than the OM model, suggesting the proposed SGFLC model almost can achieve the optimal control. Comparing to three adaptive models, the SGFLC model performs better than the IGFLC, VQ and MQ models by respectively curtailing 0.54, 3.51 and 7.02 vehicle-hours (0.93%, 6.02% and 12.03%) of total vehicle delays, demonstrating the effectiveness of our proposed stepwise GFLC model.

Table 4.4 Comparisons of control models at the experimental isolated intersection.

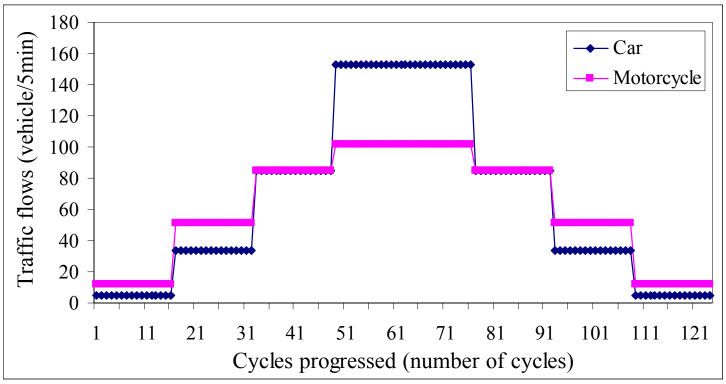
Models	*TVD* (vehicle-hours)	*ΔTVD* compared with SGFLC (vehicle-hours)	(%)
SGFLC	58.34	-	-
OS	64.81	6.47	11.09
OM	57.74	-0.60	-1.03
IGFLC	58.88	0.54	0.93
VQ	61.85	3.51	6.02
MQ	65.36	7.02	12.03

Moreover, according to the learning results of two similar GFLC models, the SGFLC and IGFLC, as shown in Table 4.5, although both GFLC models exhibit high control performance, the proposed SGFLC model selects much fewer rules (only five rules) with a relatively fewer generations than the IGFLC model does (374 rules). Additionally, by examining the rules selected by the IGFLC model, many of them are redundant or mutually conflicting. The merit of selecting few rules provides a chance for post-optimization adjustment and rule interpretation. Thus, the comparison shows that the proposed SGFLC is more effective, efficient and comprehensible than the IGFLC model.

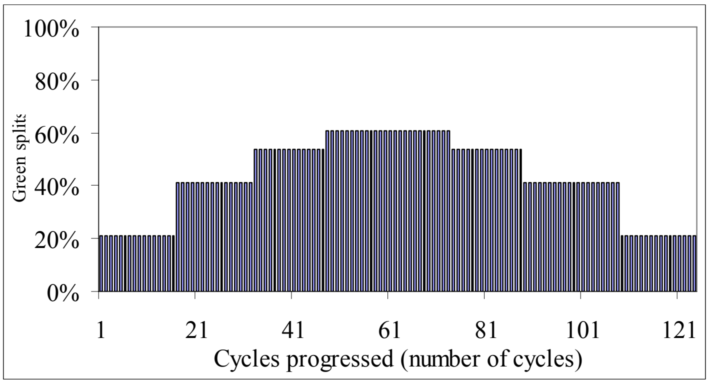
Table 4.5 Learning results of the SGFLC and IGFLC models.

Models	State variables	Generations	*TVD*	Number of selected rules
SGFLC	*TFC,TFM,QLC* and *QLM*	75	58.34	5
IGFLC	*TFC,TFM,QLC* and *QLM*	383	58.88	374

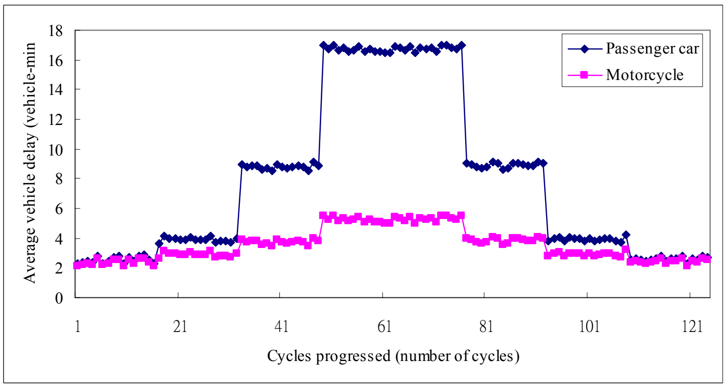
The green splits determined by the SGFLC model are depicted in Figure 4.6 (b), which are in coincidence with the traffic patterns in Figure 4.6 (a), suggesting that the proposed SGFLC can control the signal responsively. Figure 4.6(c) further presents the average delays of cars and motorcycles. As the traffic grows, the average delays of both cars and motorcycles are significantly increased. It is interesting to note that the average delay of cars grow much more rapidly than that of motorcycles, because motorcyclists do not follow the lane disciplines. They may make lateral drifts breaking into two moving cars. Once blocked by the front vehicles, they even make wide transverse crossings through the gap between two stationary cars in the same lane, in order to keep moving forward. The behaviors are in accordance with our field observations and the cellular automaton model proposed by Lan *et al*. (2010).



(a) Traffic flow rates of cars and motorcycles



(b) Green splits

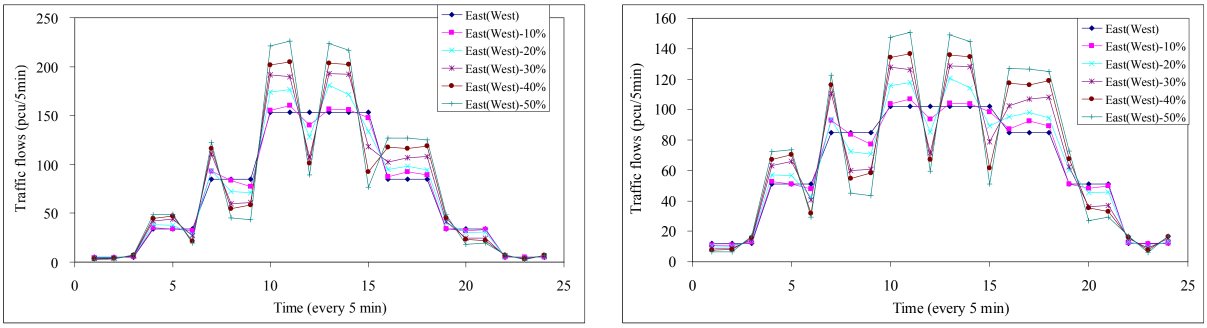


(c) Average delays of cars and motorcycles

Figure 4.6 Traffic flow rates, green splits and average delay of east-west traffic.

To further examine the robustness of the SGFLC model, we randomly vary the traffic flows by 10% to 50% as shown in Figure 4.7. Assume that timing plans of pre-timed models (i.e. the OS and OM) remain unchanged and the adaptive models follow the same rules learned from the original traffic patterns given in Figure 4.4. The results are summarized in

Table 4.6. Note that the SGFLC model performs best among the pre-timed and adaptive models. Moreover, the SGFLC model can do much better than any other models as the traffic flows vary more conspicuously, indicating the robustness of the SGFLC model.



(a) car flow rates (b) motorcycle flow rates

Figure 4.7 Varied five-minute flow rates at the experimental isolated intersection.

Table 4.6 Comparisons of control performance with randomly varied flow rates.

Models	10%		20%		30%		40%		50%	
	TVD	*ΔTVD%*	*TVD*	*ΔTVD%*	*TVD*	*ΔTVD%*	*TVD*	*ΔTVD%*	*TVD*	*ΔTVD%*
SGFLC	61.41	-	61.74	-	66.05	-	67.88	-	70.57	-
OS	69.82	13.69	77.73	25.90	84.54	27.99	89.40	31.70	95.97	35.99
OM	65.55	6.74	66.89	8.34	72.15	9.24	77.10	13.58	83.89	18.87
IGFLC	63.05	2.67	65.67	6.37	70.43	6.63	72.68	7.07	76.34	8.18
VQ	63.50	3.40	67.70	9.65	72.80	10.22	75.01	10.50	78.13	10.71
MQ	66.11	7.65	67.22	8.88	72.35	9.54	77.98	14.88	84.19	19.30

The sensitivity analysis of different percentages of turning flow is shown in Table 4.7. The timing plans of all signal control models also remain unchanged. Note that the SGFLC has outperformed over than other timing plans in each level of turning flow rates except training case (P_{LT}=0.2, P_{RT}=0.2). Moreover, the SGFLC can do much better than any other models as the turning flows increase.

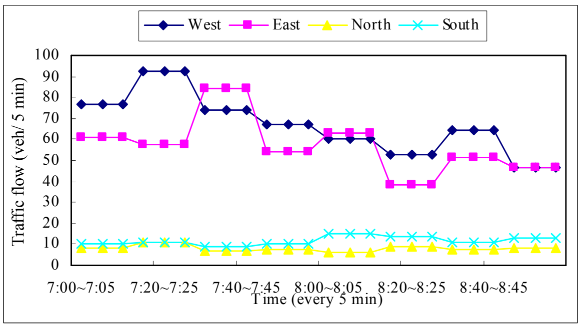
Table 4.7 Comparison of control performance with increased turning flow rates.

Models	P_{LT} (P_{RT}=0.2 P_S=1- P_{LT}- P_{RT})					
	0.2		0.4		0.6	
	TVD	*ΔTVD%*	*TVD*	*ΔTVD%*	*TVD*	*ΔTVD%*
SGFLC	58.34	-	73.68	-	92.92	-
OS	64.81	11.09	97.49	32.32	125.93	35.53
OM	57.74	-1.03	88.16	19.65	117.54	26.50
IGFLC	58.88	0.93	74.85	1.59	94.98	2.22
VQ	61.85	6.02	89.34	21.25	114.05	22.74
MQ	65.36	12.03	93.14	26.41	122.00	31.30
Models	**P_{RT} (P_{LT}=0.2 P_S=1- P_{LT}- P_{RT})**					
	0.2		0.4		0.6	
	TVD	*ΔTVD%*	*TVD*	*ΔTVD%*	*TVD*	*ΔTVD%*
SGFLC	58.34	-	72.09	-	86.09	-
OS	64.81	11.09	85.85	19.09	107.60	24.99
OM	57.74	-1.03	72.83	1.03	89.56	4.03
IGFLC	58.88	0.93	72.24	0.21	88.63	2.95
VQ	61.85	6.02	85.93	19.20	102.37	18.91
MQ	65.36	12.03	89.35	23.94	114.99	33.57

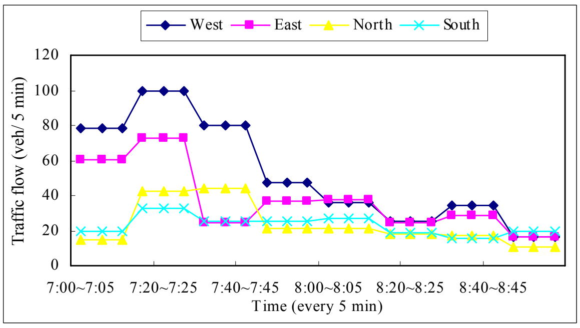
4.5 A Field Case

4.5.1. Data

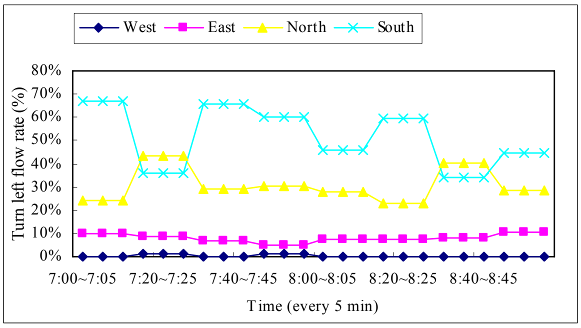
To validate the applicability of proposed stepwise GFLC model, a field study at the signalized intersection of Jin-Ma Road and Chang-He Road in Changhua City in Taiwan is conducted. Five-minute flow rates from 7:00 a.m. to 9:00 a.m. are surveyed as shown in Figure 4.8. The green time of currently operated timing plan during the observed time period is 95 seconds in west-east direction and 35 seconds in north-south direction, with all red + lost time =6 seconds. The information of field case study was shown in table 4.8.



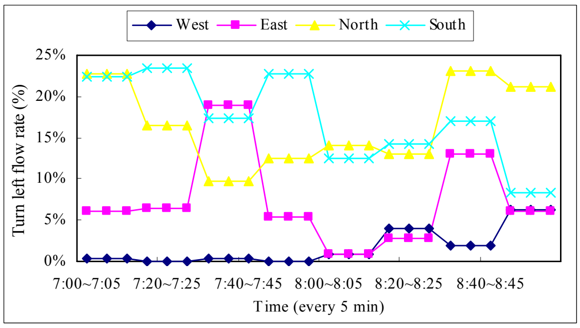
(a) total car flow rates



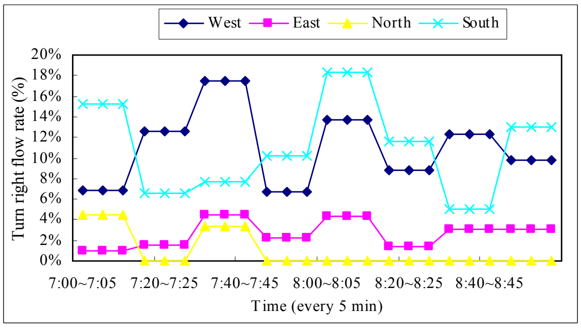
(b) total motorcycle flow rates



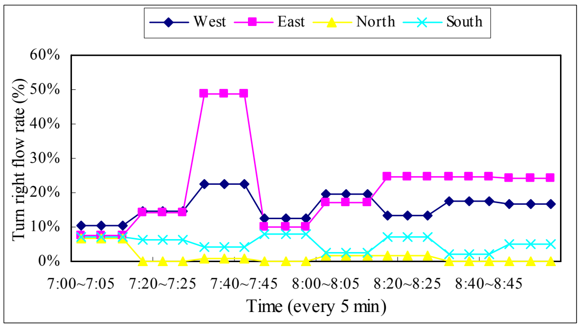
(c) turn left car flow rates



(d) turn left motorcycle flow rates



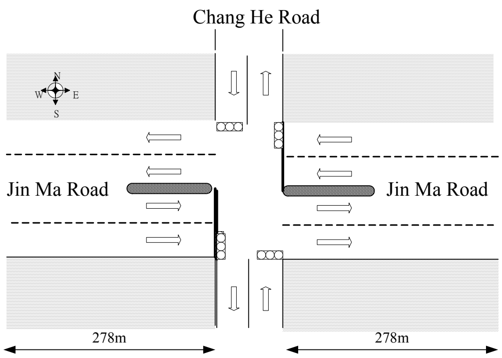
(e) turn right car flow rates



(f) turn right motorcycle flow rates

Figure 4.8 Five-minute flow rates at field-study in Changhua.

Table 4.8 Data information of field case study in isolated intersection.

Configuration		
Timing plain	Ease-West bound	North-South bound
	95 sec.	45 sec.
Number of lanes	Ease-West bound	North-South bound
	2	1
Coordinated strategy	-	

4.5.2. Results

The comparison of control performance between SGFLC, IGFLC, VQ, MQ and current timing plan is reported in Table 4.9. Note that the total vehicle delay for SGFLC is 52.38 vehicle hours, which is far less than the current timing plan in operation, IGFLC, VQ and MQ by 10.33, 0.76, 3.15 and 6.30 vehicle hours (19.72%, 1.45%, 6.01% and 12.03%), respectively.

Table 4.9 Comparison of control performance at field-study in Changhua.

Timing plan	*TVD* (vehicle-hours)	*ΔTVD* compared with SGFLC	
		(vehicle-hours)	(%)
SGFLC	52.38	-	-
IGFLC	53.14	0.76	1.45
VQ	55.53	3.15	6.01
MQ	58.68	6.30	12.03
Current timing plan	62.71	10.33	19.72

4.6 Discussions

According to the learning results of two similar GFLC models (IGFLC and SGFLC), although both GFLC models exhibit high control performance, the proposed SGFLC model selects much fewer rules (only five rules) with a relatively fewer generations than the IGFLC model does (374 rules). This result demonstrates the IGFLC tend to select some redundant or conflicting rules. On the other hand, the IGFLC model requires a total of 383 generations, each of which contains 100 populations, for convergence, making a total of 38,300 iterations have to be conducted. Comparing to the SGFLC model, there are only 75 generations with a total of 7,500 iterations for convergence. Thus, the SGFLC model is much more efficient than the IGFLC model. Additionally, by examining the rules selected by the IGFLC model, many of them are conflicting with each other. Take Rule 273 and Rule 298 selected by the IGFLC model for example:

Rule 273:*TFC=3*, *QLC=4, TFM=1, QLM=5* then *EGT= 3*

Rule 299: *TFC=3*, *QLC=4, TFM=2, QLM=5* then *EGT= 1*

The linguistic degree of motorcycle traffic flow in Rule 273 is lower than that of Rule 299 by holding the linguistic degree of other state variables the same, the linguistic degree of *EGT* of Rule 273 should be less than that of Rule 299. However, the selected two rules are obviously conflicting.

As to the selected rules of SGFLC models, Rule 1 can curtail the total vehicle delays to the largest amount and the rule considers *TFC* from 780~1,700 vehicles/hr, *QLC* from 7~42 vehicles, *TFM* from 643~1,323 vehicles/hr, *QLM* from 6~13 vehicles and *EGT* from 4~6 seconds. These values of state variables approximately reflected the highest traffic patterns in Figure 4.4.

By randomly varying the traffic flows from 10% to 50%, the total vehicle delays only increase from 0.54% to 14.92%. For sensitivity analysis of different percentages of turning flow, the total vehicle delays respectively increase 59.27% and 47.57% as P_{LT} and P_{RT} grow 3 times. Note that the selected rules of the SGFLC model remain unchanged. Those results shown proposed model can effectively control the traffic signal. Additionally, the increase in the turning flow ratio also show a negative impact to the intersection delay.

Chapter 5 SEQUENTIAL INTERSECTIONS

This study further extends the proposed SGFLC model to the signal control of consecutive intersections. These sequential intersections contain an arterial (east-west direction) and three competing approaches (north-south direction). To synchronize the signal control for the sequential intersections, three coordinated signal systems including simultaneous, alternate, and progressive strategies are considered. The simultaneous strategy implements exactly the same signal timing plans simultaneously in sequential intersections without offset (time lag). The progressive strategy implements these plans with offset. The alternative strategy implements two timing plans with inverse green and red times. In addition, an independent operation which implements the timing plans at the sequential intersections without any coordination is also compared. The timing plans of these four signal systems are determined by the SGFLC, IGFLC, VQ and MQ models, respectively.

5.1 Parameter Settings and Traffic Data

To validate the effectiveness and robustness of the proposed SGFLC signal control model, an experimental example with three consecutive four-leg intersections (Figure 5.1) is demonstrated. The percentages of turning flow along an arterial are setting as: left turning (P_{LTA})=0.2, right turning (P_{RTA})=0.2. The percentages of turning flow along with competing approaches are setting as: left turning (P_{LTC})=0.1, right turning (P_{RTC})=0.1. The parameters of the MCTM are set as: free-flow speed=50km/h, time step=2 seconds, k_j=130 veh/km/lane. Assume that the intersection has two lanes ($N_i(t)$=3.6 cars/cell for all i and t) in each approach with saturation flow of 1800 pcu/hr/lane ($q_{mi}(t)$=2.00 veh/time step for all i and t). The distance between intersections 1 and intersection 2 is 139 meters (5 cells). The distance between intersections 2 and intersection 3 is 222 meters (8 cells). The five-minute flow rates in different approaches are shown in Figure 5.2. Noticeable peak and off-peak traffic patterns are assumed in east and west directions. The offset of progressive coordinated strategy are 10 seconds and 16 seconds, since the free flow travel speed between intersections is set as 50 km/hr. The parameters of the SGFLC model are set as population size=100, crossover rate=0.9, mutation rate=0.05, a=0.3, h=0.5, η=80%, ε=0.05. The center of gravity method is employed for defuzzification. The parameters of signal control are: G_{max}=100 seconds, G_{min}=20 seconds, all red + lost time =6 seconds, EGT_{max}=20 seconds, and EGT_{min}=4 seconds.

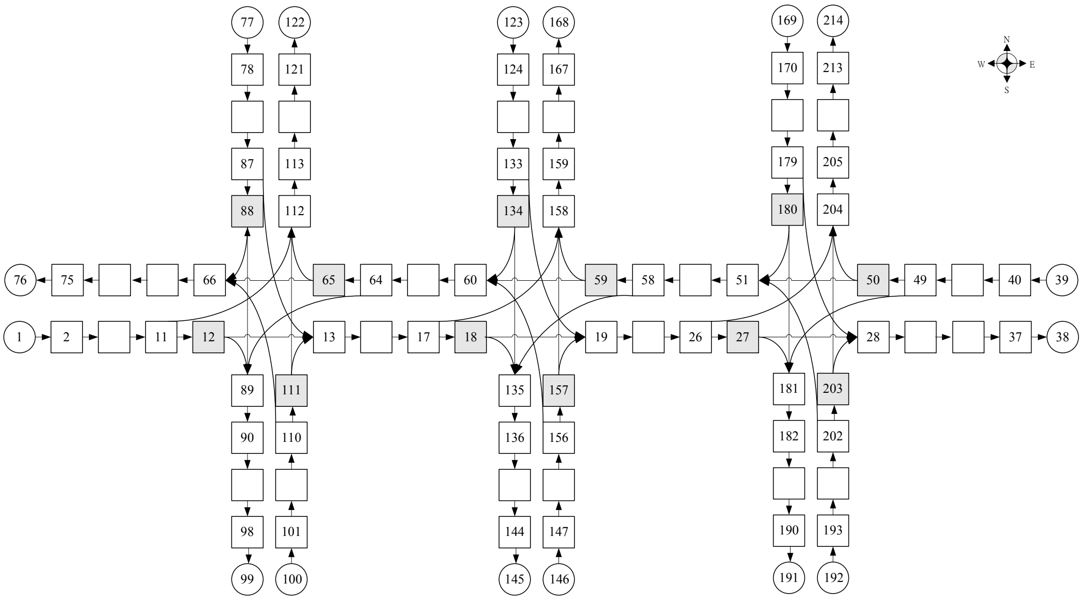
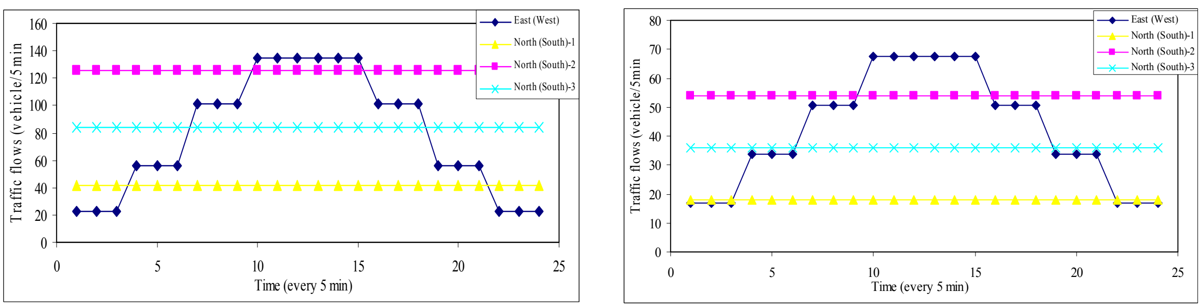


Figure 5.1 Configuration of the experimental sequential intersections.



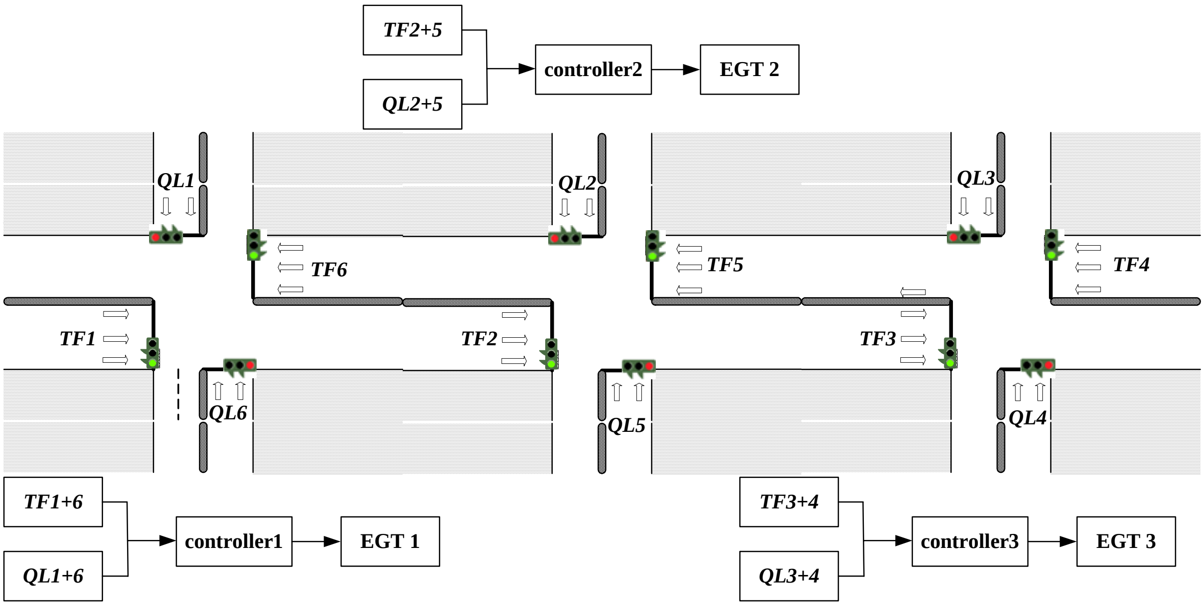
(a) car flow rates (b) motorcycle flow rates

Figure 5.2 Five-minute flow rates at the experimental sequential intersections.

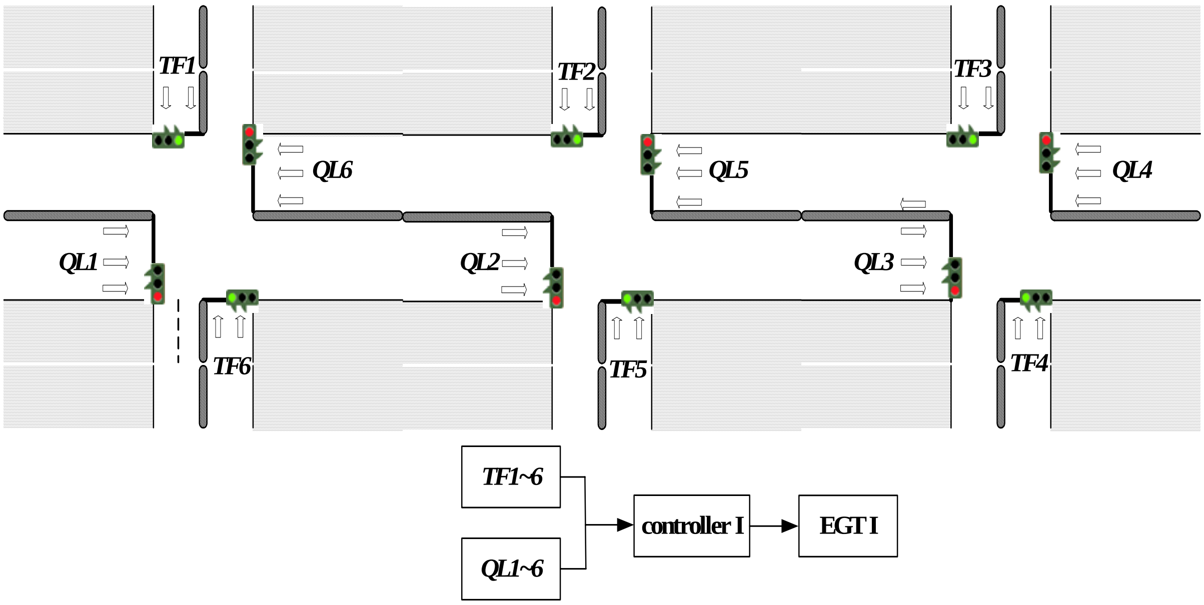
5.2 Model Training and Performance

The difference of signal control between an isolated intersection and coordinated sequential intersections is that the control variable (*EGT*) of an isolated intersection is determined based on the state variables considering the traffic condition at the intersection alone while the *EGT* of coordinated sequential intersections is determined based on the traffic conditions of all approaches along the arterial.

An arterial coordinated signal control and training structure are shown in Figure 5.3. To reflect the various traffic conditions of different coordinated intersections, the green times along the arterial are independently determined by following the same control mechanism of an isolated intersection. However, to synchronize the signal timing plans of all coordinated intersections, an integrated signal control mechanism by considering the summation of traffic flows at all approaches in green phase and summation of queen length at all approaches in red phase. Therefore, the cycle length of all coordinated intersections is kept the same.



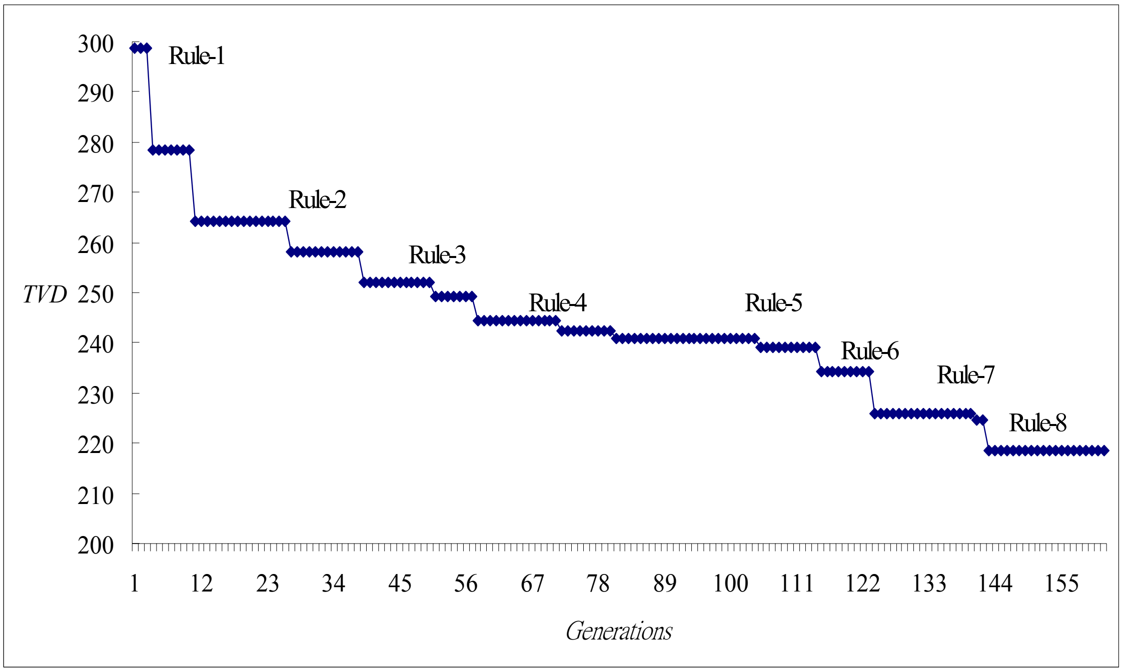
(a) Arterial approach green time control



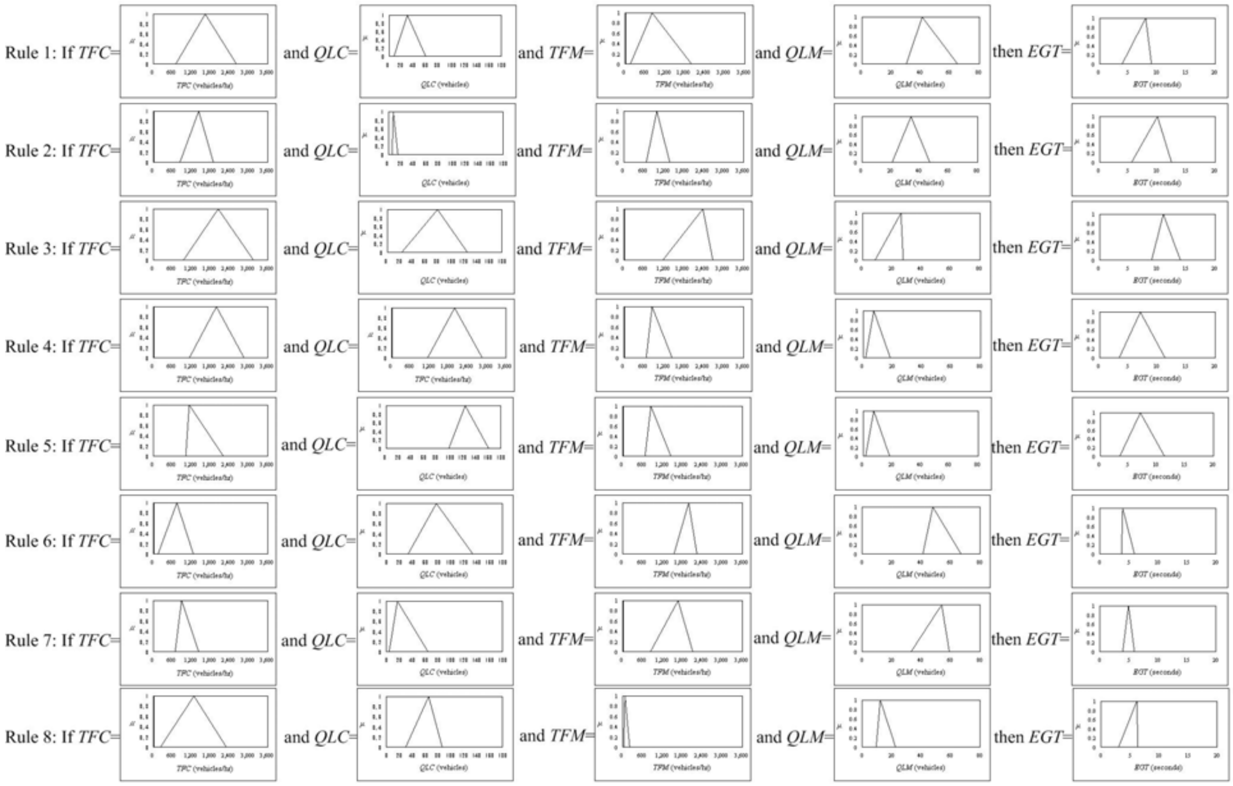
(b) Competing approach green time control

Figure 5.3 Arterial coordinated signal control system structure.

Take progressive coordinated strategy for example. The signal control rules for arterial approaches are mentioned in Chapter 4. The learning process of competing approaches is depicted in Figure 5.4(a). Note that SGFLC converges after five stepwise evolutions with a total of 162 generations progressed. The value of *TVD* decreases from 298.74 to 218.55 veh-hour. A total of five rules are selected after eight stepwise evolutions. Figure 5.4(b) presents the optimally selected eight logic rules along with corresponding tuned membership functions.



(a) Learning process



(b) Selected logic rules and tuned membership functions

Figure 5.4 Learning process and results of the SGFLC model at competing approaches.

5.3 Model Validation and Comparisons

To validate the effectiveness, the control performance of the SGFLC model is compared with the IGFLC, VQ and MQ models. The control performances of these control models are reported and compared in Table 5.1. Obviously, the performances under progressive coordinated strategy are significantly superior to other systems. The progressive SGFLC model performs best among these four models, follows by the progressive VQ model. The signal control models under alternate coordinated strategy perform relatively poor. Also notice that all the SGFLC models under various coordinated strategies perform better than the IGFLC, VQ and the MQ models. The results show the effectiveness of the proposed SGFLC model in controlling the signal timings of sequential intersections.

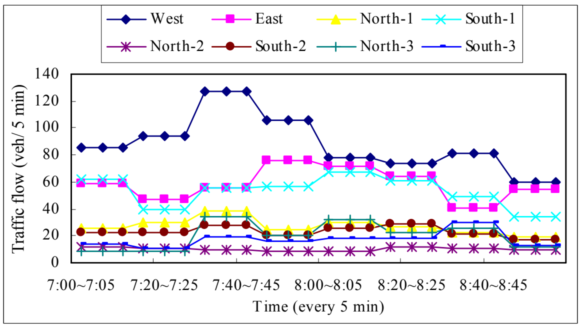
Table 5.1 Comparison of control performance at the experimental intersections.

Signal coordinated strategy	*TVD* (vehicle-hours)				Rate of *ΔTVD* reduced by SGFLC		
	SGFLC	IGFLC	VQ	MQ	IGFLC	VQ	MQ
Simultaneous	234.16	238.64	239.98	246.46	1.91%	2.49%	5.25%
Progressive	218.55	225.71	225.52	231.54	3.28%	3.19%	5.94%
Alternate	282.00	284.80	287.55	293.03	0.99%	1.97%	3.91%
Independent	249.23	252.01	252.77	259.05	1.12%	1.42%	3.94%

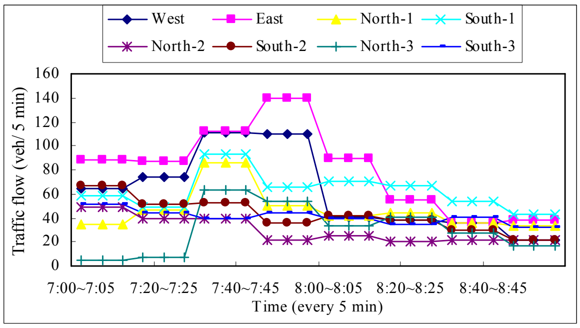
5.4 A Field Case

5.4.1. Data

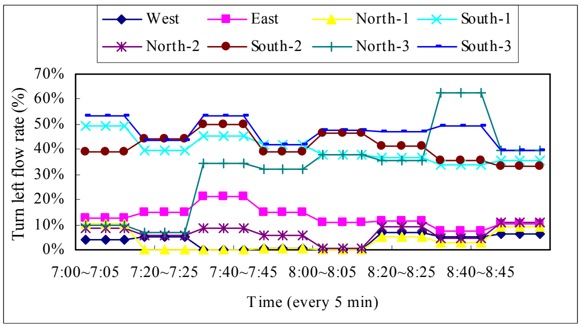
The proposed SGFLC signal control model is further applied to a real case of three adjacent signalized intersections in Jin-Ma arterial intersected with Chang-Mei Road, Chang-Xing Road and Dong-Gu Road of Changhua City in Taiwan. Table 5.2 depicts the configuration of this arterial and three streets, in which Jin-Ma Road is a two-lane arterial in west-east direction, Chang-Mei Road, Chang-Xing Road and Dong-Gu Road are all one-lane streets in north-south direction. Five-minute flow rates during the morning peak hours from 7:00 a.m. to 9:00 a.m. are surveyed as shown in Figure 5.5. The green times of current timing plans during the observed period are 40 seconds north-south and 75 seconds west-east at Jin-Ma/Chang-Mei intersection, 50 seconds north-south and 120 seconds west-east at Jin-Ma /Chang-Xing intersection, 50 seconds north-south and 125 seconds west-east at Jin-Ma /Dong-Gu intersection. All-reds and change interval are 6 seconds for all intersections. Currently, there is no signal coordinated control between these three intersections.



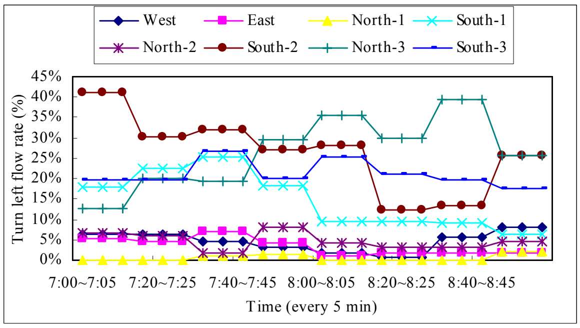
(a) total car flow rates



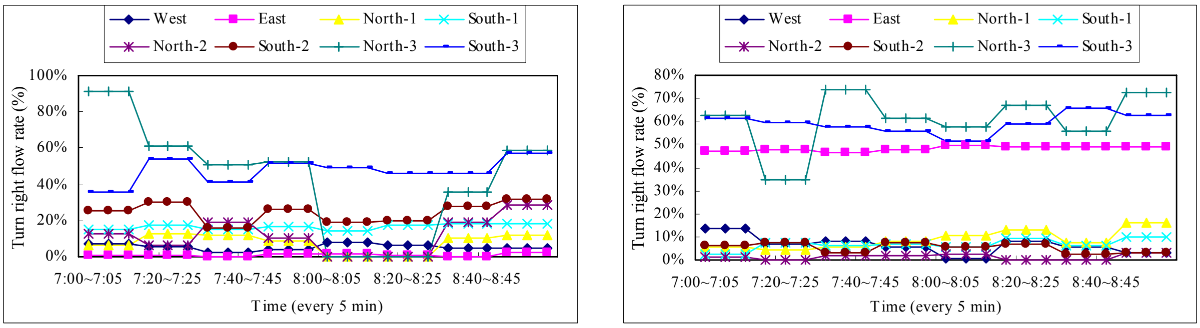
(b) total motorcycle flow rates



(c) turn left car flow rates



(d) turn left motorcycle flow rates

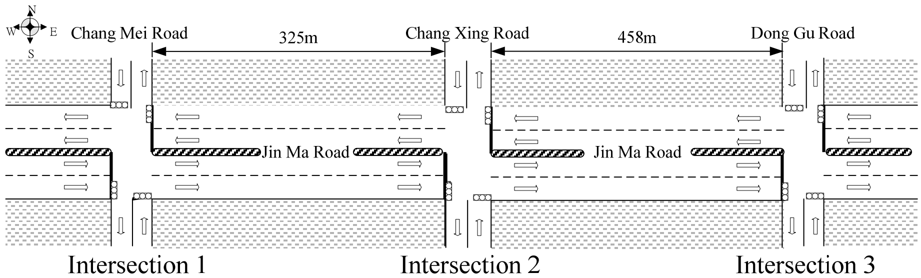


(e) turn right car flow rates (f) turn right motorcycle flow rates

Note: north-# and south-# represent the traffic flows in north and south directions, respectively, at intersection #.

Figure 5.5 Five-minute flow rates at the field-study in Changhua.

Table 5.2 Data information of field case study at 3 sequential intersections.

Configuration		
Timing plain	Jin-Ma/Chang-Mei intersection	
	Ease-West bound	North-South bound
	75 sec.	40 sec.
	Jin-Ma /Chang-Xing	
	120 sec.	50 sec.
	Jin-Ma /Dong-Gu	
	125 sec.	50 sec.
Number of lanes	Arterial approach	Competing approach
	2	1
Coordinated strategy	Independent	

5.4.2. Results

The control performances of SGFLC, IGFLC, VQ, MQ and current timing plan are reported in Table 5.3. Compared with the current timing plan that is operated independently, the progressive SGFLC can curtail the total vehicle delays by the largest amount (19.08%), followed by progressive IGFLC and VQ (16.52% and 15.49%), and with the least reduction (1.49% and 0.32%) by alternate signal system. Also notice that SGFLC consistently outperforms over other single models, no matter which signal system is operated.

Table 5.3 Comparison of control performance at the sequential intersections in Changhua.

Signal coordinated strategy	*TVD* (vehicle-hours)				
	SGFLC	IGFLC	VQ	MQ	Current timing plan
Simultaneous	318.58(12.13%)	324.84(10.41%)	328.30(9.45%)	336.50(7.19%)	-
Progressive	293.41(19.07%)	302.66(16.52%)	306.41(15.49%)	316.24(12.78%)	-
Alternate	349.76(3.53%)	353.66(2.46%)	357.17(1.49%)	361.43(0.31%)	-
Independent	339.30(6.42%)	345.87(4.61%)	352.85(2.68%)	356.25(1.74%)	362.57

Note: the percentages in parenthesis represent the rates of *TVD* reduction compared with the current timing plan.

5.5 Discussions

According to the selected rules of the SGFLC model under a progressive coordination system, Rule 1 can curtail the total vehicle delays to the largest amount and it considers *TFC* from 702~2,613 vehicles/hr, *QLC* from 8~58 vehicles, *TFM* from 159~2,011 vehicles/hr, *QLM* from 30~65 vehicles and *EGT* from 4~9 seconds. The linguistic degrees of state variables and control variable of Rule 1 are shown below:

Rule 1: IF: *TFC=6*, *QLC=3, TFM=2, QLM=5* then *EGT= 5*

Based on the Rule 1, Rule 2 can reduce the TVD from 258 to 252 vehicle-hours and it considers *TFC* from 843~1,896 vehicles/hr, *QLC* from 6~15 vehicles, *TFM* from 675~1,389 vehicles/hr, *QLM* from 21~47 vehicles and *EGT* from 6~12 sec. The linguistic degrees of state variables and control variable of Rule 2 are shown below:

Rule 2: IF: *TFC=5*, *QLC=1, TFM=4, QLM=4* then *EGT= 7*

The linguistic degrees of state variables and control variable of other rules are also shown below. Note that Rule 1 to Rule 4 aims to control signal under high traffic flow conditions while Rule 5 to Rule 8 aims to deal with longer queue length. Additionally, as investigating into the rules, the linguistic level of control variable, *EGT*, increases as traffic flow grows and queue length becomes shorter. The selected rules are logically reasonable.

Rule 3: IF: *TFC=8*, *QLC=6, TFM=7, QLM=3* then *EGT= 8*

Rule 4: IF: *TFC=7*, *QLC=7, TFM=8, QLM=8* then *EGT= 6*

Rule 5: IF: *TFC=3*, *QLC=8, TFM=3, QLM=1* then *EGT= 4*

Rule 6: IF: *TFC=1*, *QLC=5, TFM=6, QLM=6* then *EGT=1*

Rule 7: IF: *TFC=2*, *QLC=2, TFM=5, QLM=7* then *EGT= 2*

Rule 8: IF: *TFC=4*, *QLC=4, TFM=1, QLM=2* then *EGT= 3*

Chapter 6 DETERMINING THE COORDINATED INTERSECTIONS

The control performance of signal coordination would be greatly degraded as the number of coordinated intersections increases. Thus, numerous studies attempted to determine the optimal number of neighboring intersections to be coordinated. Therefore, this study adopts GAs to determine which intersections to be coordinated and how many clusters of coordinated intersections would be.

6.1 Model Structure

A corridor adaptive coordinated signal control is shown in Figure 6.1. The structure divided into two processes. The learning process of isolated intersection and sequential intersections were mentioned above. The control process includes 2 kinds of controller. To reflect the various traffic conditions of different coordinated intersections, the green times along the arterial are independently determined by following the same control mechanism of an isolated intersection. However, to synchronize the signal timing plans of all coordinated intersections, an integrated signal control mechanism by considering the summation of traffic flows at all approaches in green phase and summation of queen length at all approaches in red phase. Therefore, the cycle length of all coordinated intersections is kept the same. According to the analysis above, the performances under progressive coordinated strategy are significantly superior to other systems. This coordinated strategy was adopted further elaborated and compared. Note that the mining rules of SGFLC signal control models both for isolated intersection and sequential intersections also remain unchanged.

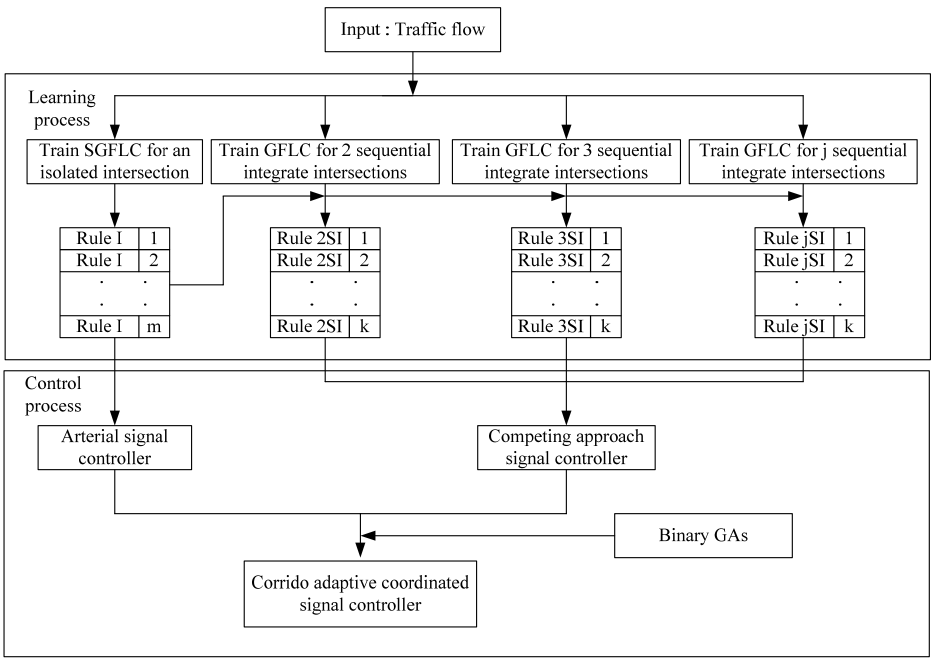
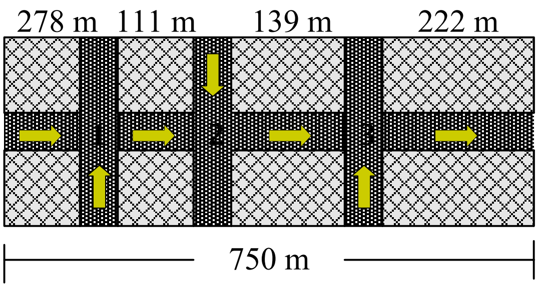


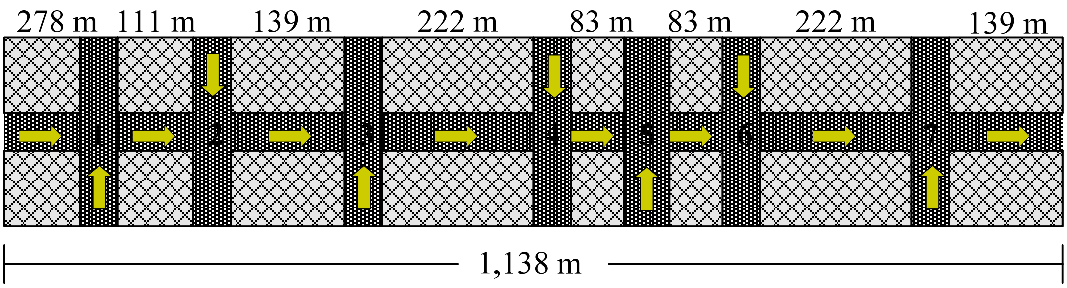
Figure 6.1 The structure of a corridor adaptive coordinated signal control model.

6.2 Parameter Setting and Traffic Data

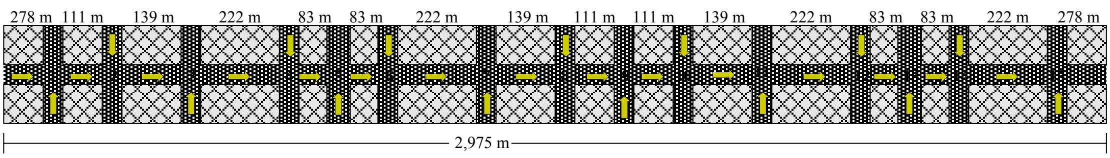
This study introduces three sizes of arterial to combine proposed SGFLC model. The small size arterial consists of three intersections (Figure 6.2 (a)). An experimental example with seven and fifteen consecutive four-leg intersections (Figure 6.2 (b) and Figure 6.2 (c)) is demonstrated as medium-sized and large-sized arterials, respectively. The traffic flow rates in different approaches with three sizes of arterial are shown in Figure 6.3 (a) to Figure 6.3 (c), respectively. Note that two types of traffic flow pattern are adopted in this experimental case and assumes each approaches being one-way direction. The percentages of turning flow are setting as: arterial approaches=0.1 and competing approaches=0.5. Each of types is divided into peak and off-peak hour. Also note that the competing approaches traffic are assumed as flat in type I and as different in type II. As shown in Figure 6.3, intersections 2, 4 and 8 may be the critical intersections along the arterial. To simplify the analysis, this study neglects the turning traffic and coordinates intersections by the progressive signal system only.



(a) three sequential intersections

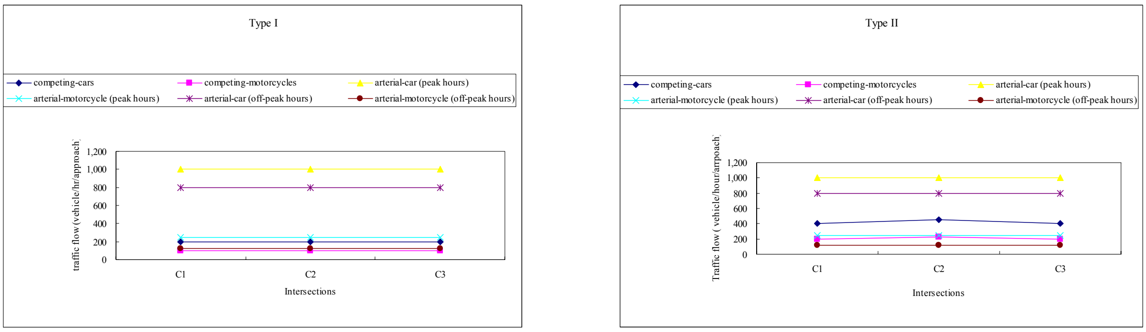


(b) Seven sequential intersections

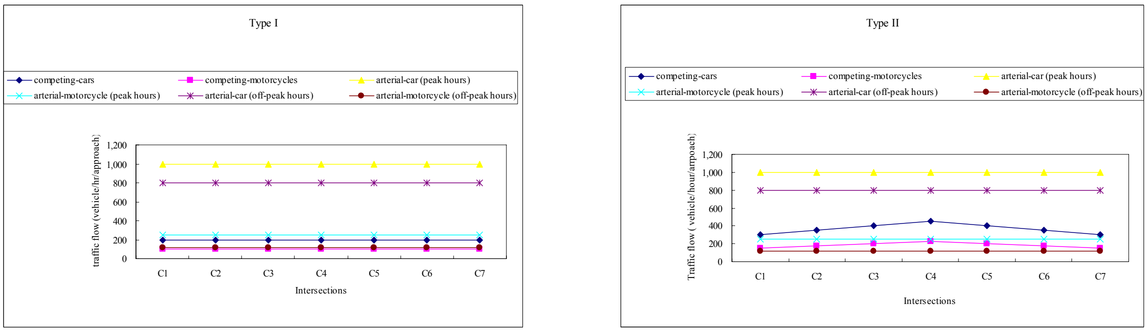


(c) Fifteen sequential intersections

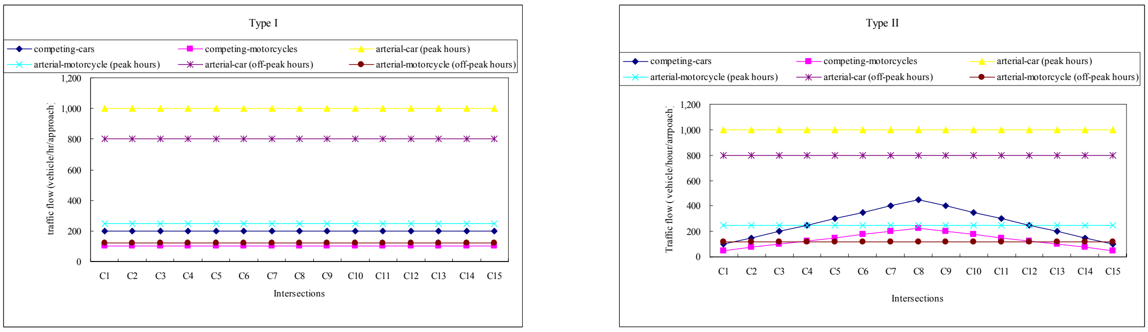
Figure 6.2 Configuration of the corridor intersections.



(a) three sequential intersections



(b) Seven sequential intersections



(c) Fifteen sequential intersections

Figure 6.3 Traffic flow rates at the corridor intersections.

6.3 Method Validation and Comparison

To validate the effectiveness, the control performance of SGFLC model and GAs clusters (SGFLC+GAs) is compared with coordinated guidance: SGFLC hybrid guidance (SGFLC+G). The guidance can be referred to any textbook in traffic control (e.g. Manual on Uniform Traffic Control Devices, FHA, 2009). The MUTCD provides the guidance that traffic signals within 800 meters (0.5 miles) of each other along a corridor should be coordinated unless operating on different cycle lengths. An independent operation with SGFLC (SGFLC+I) which implements the timing plans at the corridor intersections without any coordination is also compared. On the other hand, appropriate coordinated intersections alone a corridor not only can enhance progressive probability but also can curtail traffic delay. Thus, Total vehicle throughput (*TVT*) including corridor and competing approaches is chosen as coordinated performance in this study. Besides, the control rules of SGFLC which under minimal total vehicle delay (*TVD*) remain unchanged.

Table 6.1 summarizes the comparison results. An independent operation which implements the timing plans at the sequential intersections without any coordination is also compared. For type I traffic pattern, the proposed SGFLC+GAs method performs the same as SGFLC+ G method in small size corridor and performs better than the SGFLC+ G and SGFLC+ I methods by respectively extending 20% and 47% total vehicle throughput for off-peak traffic and 17% and 23% for peak traffic in medium and large sizes corridors. In the case of type II traffic pattern, the experimental example has also shown that SGFLC+GAs method performs best, no matter which traffic conditions are studied. The results validate the effectiveness of our proposed SGFLC signal control model hybridizing with GA-based clustering method.

Table 6.1 Comparisons of coordinated clusters at the corridor intersections.

Size	Traffic	Coordinated method	No. of clusters	Chromosome (coordinated intersections)	*TVT* (vehicle)	*ΔTVT* compared with SGFLC+GAs (%)
				Type I		
small	Off-peak	SGFLC+GAs	1	111	1,507	-
		SGFLC+G	1	1+2+3	1,507	0.00%
		SGFLC+ I	3	1-2-3	1,003	33.44%
	peak	SGFLC+GAs	1	111	1,837	-
		SGFLC+G	1	1+2+3	1,837	0.00%
		SGFLC+ I	3	1-2-3	1,408	23.35%
medium	Off-peak	SGFLC+GAs	1	0000000	2,516	-
		SGFLC+G	2	1+…+6-7	1,995	20.71%
		SGFLC+ I	7	1-2-3-4-5-6-7	1,327	47.26%
	peak	SGFLC+GAs	1	0000000	2,846	-
		SGFLC+G	2	1+…+6-7	2,351	17.39%
		SGFLC+ I	7	1-2-3-4-5-6-7	2,181	23.37%
large	Off-peak	SGFLC+GAs	3	111111000001111	4,340	-
		SGFLC+G	3	1+…+6-7+…+12-13+…+15	3,412	21.38%
		SGFLC+ I	15	1-2…-15	2,889	33.43%
	peak	SGFLC+GAs	4	111000011110000	4,670	-
		SGFLC+G	3	1+…+6-7+…+12-13+…+15	3,857	17.41%
		SGFLC+ I	15	1-2…-15	3,579	23.36%
				Type II		
small	Off-peak	SGFLC+GAs	1	111	2,482	-
		SGFLC+G	1	1+2+3	2,482	0.00%
		SGFLC+ I	3	1-2-3	1,966	20.79%
	peak	SGFLC+GAs	1	111	2,812	-

		SGFLC+G	1	1+2+3	2,812	0.00%
		SGFLC+ I	3	1-2-3	2,223	20.95%
medium	Off-peak	SGFLC+GAs	2	0001111	4,241	-
		SGFLC+G	2	1+…+6-7	3,558	16.10%
		SGFLC+ I	7	1-2-3-4-5-6-7	2,817	33.58%
	peak	SGFLC+GAs	1	0001111	4,571	-
		SGFLC+G	2	1+…+6-7	3,839	16.01%
		SGFLC+ I	15	1-2-3-4-5-6-7	3,612	20.98%
large	Off-peak	SGFLC+GAs	4	111111101110000	5,765	-
		SGFLC+G	3	1+…+6-7+…+12-13+…+15	4,836	16.11%
		SGFLC+ I	7	1-2…-15	4,566	20.80%
	peak	SGFLC+GAs	6	111000010001110	6,095	-
		SGFLC+G	3	1+…+6-7+…+12-13+…+15	5,119	16.01%
		SGFLC+ I	15	1-2…-15	4,817	20.97%

Note: 1. GFLC+GAs means the combination of SGFLC signal control model with GAs coordinated method.

2. GFLC+G means the combination of SGFLC signal control model with coordinated guidance provide by MUTCD.

3. GFLC+I means the combination of SGFLC signal control model with independent coordinated operated.

6.4 Discussions

As noted from the analytical results, signalized intersections can increase total vehicle throughput through a proper coordination. For the small-sized corridors, the proposed hybrid model tends to coordinate all intersections, no matter which traffic pattern conditions are. For the medium-sized corridors, the traffic patterns at the competing approaches could affect the intersection coordination result. For the large-sized corridors with 15 intersections, both traffic patterns of competing approaches and of the arterial approach determine the coordination result. Additionally, the distance between intersections may also show its effect to for the intersection clustering result. Moreover, it is interesting to note that the number of coordinated intersections will not exceed 7 intersections. This finding is in accordance with the conclusions proposed by Zong and Thomas (2007).

Chapter 7 CONCLUDING REMARKS

The summary of the academic and practical contributions and major findings of this study is given in Section 7.1. Limitations of this research are arranged in Section 7.2. Suggestions for further research are then drawn in Section 7.3.

7.1 Conclusions

This study develops a self-learning traffic signal control model for both isolated and sequential intersections based on the MCTM traffic simulator. The contributions and findings related to this research are summarized in the following points:

1. Following most of the previous literatures, for the case of an isolated intersection, we choose traffic flow in green phase (*TF*) and queue length in red phase (*QL*) as two state variables and extension of green time (*EGT*) as the control variable and total vehicle delays (*TVD*) as performance measurement. For the case of sequential intersections of competing approaches, *TF* is the summation of traffic flows at all approaches in green phase; while *QL* is the summation of queen length at all approaches in red phase.

2. This study establishes an arterial coordinated signal control with a self-training capacity. To reflect the various traffic conditions of different coordinated intersections, the green times along the arterial are independently determined by following the same control mechanism of an isolated intersection. However, to synchronize the signal timing plans of all coordinated intersections, an integrated signal control mechanism by considering the summation of traffic flows at all approaches in green phase and summation of queen length at all approaches in red phase. Therefore, the cycle length of all coordinated intersections is kept the same.

3. Based on the iterative GFLC model proposed by Chiou and Lan (2005), this research further develops stepwise GFLC signal control model. For the case of isolated intersection, the experimental example had shown that the control performance of SGFLC is almost the same as the optimal multiple timing plan and superior to the optimal single, IGFLC model, vanishing queue and maximum queue. Moreover, the SGFLC model can do much better than any other models as the traffic flows vary more conspicuously, indicating the robustness of the SGFLC model. The field case study also shows that SGFLC consistently outperforms over other single models and current timing plain. In the case of sequential intersections, both experimental example and field study have also shown that SGFLC performs better than other adaptive signal control models, no matter which coordinated signal system is operated. Those results present evidence

that GFLC is effective, robust and applicable to signal control for the intersections.

4. The validation results of the MCTM demonstrate its capability in replicating the mixed traffic behaviors at the signalized intersection. It is interesting to note that although both average delays of cars and motorcycles would be deteriorated as traffic demand grows, the average delay of cars grow much more rapidly than that of motorcycles, suggesting that the MCTM model can simulate the behaviors of motorcycles which do not follow the lane disciplines and may make lateral drifts breaking into two moving cars in order to keep moving forward.

5. According to the learning results of two similar GFLC models (IGFLC and SGFLC), although both GFLC models exhibit high control performance, the proposed SGFLC model selects much fewer rules (only five rules) with a relatively fewer generations than the IGFLC model does (374 rules). Additionally, by examining the rules selected by the IGFLC model, many of them are redundant or mutually conflicting. The merit of selecting few rules provides a chance for post-optimization adjustment and rule interpretation. Thus, the comparison shows that the proposed SGFLC is more effective, efficient and comprehensible than the IGFLC model.

6. The proposed SGFLC model mainly relies on the traffic information including traffic flow and queue length of cars and motorcycles to adaptively control the signal. Through a proper installation of two sets of sensors near the intersections, both traffic flow and queue length can be obtained (e.g. Sun *et al*., 2011). However, for the intersections with only one set of sensors, queue length can still be estimated based on traffic flow theories, e.g. shockwave method proposed by Liu *et al*. (2009).

7. In order to avoid the control performance of signal coordination degraded as the number of coordinated intersections increases. This study combines SGFLC traffic signal control rules with GAs for optimally determining which intersections have to be coordinated along a corridor. To validate the proposed hybrid models, the coordinated guidance suggested by MUTD and independent operation are compared. The experimental example has also shown that proposed model can increase 27% and 50% total vehicle throughput for off-peak traffic and 21% and 30% for peak traffic in medium- and large-sized corridors, respectively under type I traffic pattern. In the case of type II traffic pattern, the experimental example has also shown that hybrid model performs best, no matter which traffic conditions are studied.

7.2 Limitations

1. This study chooses total vehicle delay as performance indicator. Thus, other performance

indices such as stopping probability, minimum fuel consuming and maximum throughput…etc. haven't been examined.

2. This near-optimal signal control performance and validation results are mainly based on the MCTM simulation. The set of selected rules may not work well under other simulators. Additionally, the geometric design, such as parking space, bus stop and pedestrian facility… etc, has not been considered in this study.

3. The offset of progressive strategy was setting according to free flow speed and distance between intersections for simplification. The average vehicle speed under various traffic conditions should be further considered instead.

4. For sequential coordinated intersections, the mixed-traffic behaviors are assumed the same along the corridor and validated by the real traffic data near intersections. However, the relationship between cars and motorcycles traveling at the mid-block of sections may not be the same as those behaviors near intersections.

7.3 Suggestions

Although this study has developed an effective, robust and applicable signal control models for the isolated and sequential intersections, some limitations should be mentioned and some findings are worth further studies.

1. The proposed stepwise algorithm is to select rules sequentially. However, an early selected rule may not be necessary to be the one of rules in the optimal rule combination. A post-optimization adjustment mechanism can be developed to further fine tuned the selected rules and membership functions.

2. More effective and efficient encoding methods in selecting the logic rules or tuning the membership functions or both deserve to be explored.

3. For sequential coordinated intersections, the control performance is measured by *TVD* in this paper. Other performance indices, such as maximum green band, minimum stopping rate, and maximum throughput, deserve to be adopted and examined.

4. In this study, only simple two phase signal control plan is considered. Multi-phase signal control plans with consideration of turning flows at intersections deserves to be developed.

5. The control performances of the trained SGFLC model can be further examined by commonly-adopted traffic simulation software packages, such as AIMSUN, VISSIM,

PARAMICS, and CORSIM through build-in API interfaces, prior to field installation to judge effectiveness of the proposed model.

6. The mixed-traffic condition including lumps cars and heavy vehicles all together and scaled up to the network level should be considered in the traffic simulation model so as to further enhance the applicability and comprehensiveness of the proposed model.

7. The inaccuracy of traffic information detected on urban streets is pretty common. How to conduct an optimal control based on such inaccurate and unreliable vehicle detectors is also an interesting topic deserves a further attempt.

References

1. Autey, J., Sayed, T., Esawey, M.E., 2012. Operational performance comparison of four unconventional intersection designs using micro‐simulation. *Journal of Advanced Transportation*, DOI: 10.1002/atr.181.

2. Ben-Akiva, M., Cuneo, D., Hasan, M., Jha, M., Yang, Q., 2003. Evaluation of freeway control using a microscopic simulation laboratory. *Transportation Research Part C* 11, 29-50.

3. Chiou, Y.C., Lan, L.W., 2005. Genetic fuzzy logic controller: an iterative evolution algorithm with new encoding method. *Fuzzy Sets and Systems* 152, 617-635.

4. Chiou, Y.C., Lan, L.W., 2004. Adaptive traffic signal control with iterative genetic fuzzy logic controller (GFLC). *presented at the 2004 IEEE International Conference on Networking, Sensing and Control*, 287-292, Taipei, Taiwan, March 21-23.

5. Chiou, Y.C., Hsieh, C.W., 2012. Mixed traffic cell transmission models: development and validation. *Journal of the Chinese Institute of Transportation* 24, 245-276.

6. Chiou, Y.C., Huang, Y.F., 2011. Stepwise genetic fuzzy logic signal control under mixed traffic conditions. *Proceedings of the International Conference on Advances in Highway Engineering & Transportation*, Colombo, Sri Lanka.

7. Chiou, Y.C., Wang, Y.C., 2005. Development of genetic fuzzy logic controller-based ramp metering strategies. *The 10th International Conference for Hong Kong Society of Transportation Studies,* Hong Kong, Dec.10~12, 200-209.

8. Chiou, Y.C., Wang, M.T., Lan, L.W., 2003. Adaptive bus-preemption signals with genetic fuzzy logic controller (GFLC). *Journal of the Eastern Asia Society for Transportation Studies* 5, 1745-1758.

9. Chiou, Y.C., Wang, M.T., Lan, L.W., 2005. Coordinated transit-preemption signal along an arterial: iterative genetic fuzzy logic controller (GFLC) method. *Journal of the Eastern Asia Society for Transportation Studies* 6, 2321-2336.

10. Chiou, Y.C., Wang, M.T., Lan, L.W., 2007. A novel fuzzy logic controller for Transit Signal Preemption. *The 17th International Symposium on Transportation and Traffic Theory (ISTTT)***,** London, July 23-25.

11. Daganzo, C., 1994. The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory. *Transportation Research Part B* 28, 269-287.

12. Daganzo, C., 1995. The cell transmission model, part II: network traffic. *Transportation Research Part B* 29, 79-93.

13. Dion, F., Rakha, H., Zhang, Y., 2004. Evaluation of potential transit signal priority benefits along a fixed-time signalized arterial. *Journal of Transportation Engineering* 130, 294-303.

14. Esawey, M.E., Sayed, T., 2011. Unconventional USC intersection corridors: Evaluation of potential implementation in Doha, Qatar. *Journal of Advanced Transportation* 45,

38-53.

15. Fang, F.C., Elefteriadou, L., 2010. Modeling and simulation of vehicle projection arrival–discharge process in adaptive traffic signal controls. *Journal of Advanced Transportation* 44, 176-192.

16. Herrera, F., Lozano, M., Verdegay, J.L., 1995. Tuning fuzzy logic controllers by genetic algorithms. *International Journal of Approximate Reasoning* 12, 299-315.

17. Herrera, F., Lozano, M., Verdegay, J.L., 1998. A learning process for fuzzy control rules using genetic algorithms. *Fuzzy Sets and Systems* 100, 143-158.

18. Hoyer, R. and Jumar, U., 1994. An advanced fuzzy controller for traffic lights. *Annual Review in Automatic Programming* 19, 67-72.

19. Jacob, C., Abdulhai, B., 2006. Automated Adaptive Traffic Corridor Control Using Reinforcement Learning: Approach and Case Studies. *Transportation Research Record* 1959, 67-73.

20. Kosonen, I., 2003. Multi-agent fuzzy signal control based on real-time simulation. *Transportation Research Part C* 11, 389-403.

21. Lan, L.W., Chiou, Y.C., Lin, Z.H., Hsu, C.C., 2010. Cellular automaton simulations for mixed traffic with erratic motorcycles' behaviours. *Physica A* 389, 2077-2089.

22. Lekova, A., Mikhailov, L., Boyadjiev, D., Nabout, A., 1998. Redundant fuzzy rules exclusion by genetic algorithms. *Fuzzy Sets and Systems* 100, 235-243.

23. Lighthill, M.J., Whitham, J.B., 1955. On kinematic waves. I. folw movement in long rivers. II. A theory of traffic flow on long crowded reads. *Proceedings of Royal Society*, London, 281-345.

24. Lin, L.T., Tung, L.W., Ku, H.C., 2010. A synchronized signal control model for maximizing progression along an arterial. *Journal of Transportation Engineering* 136, 727-735.

25. Lin, W.H., Ahanotu, D., 1995. *Validating the basic cell transmission model on a single freeway link*. Technical note, UCB-ITS-PATH-TN-95-3, University of California, Berkeley , CA, USA.

26. Lin, W.H., Lo, H.K., 2008. A robust quasi-dynamic traffic signal control scheme for queue management. *Proceedings of the Thirteenth International Conference of Hong Kong Society for Transportation Studies*, Hong Kong: 563-572.

27. Liu, H.X., Oh, J.S., Recker, W., 2002. Adaptive signal control system with online performance measure for a single intersection. *Transportation Research Record* 1811, 131-138.

28. Liu, H.X., Wu, X., Ma, W., Hu, H., 2009. Real-time queue length estimation for congested signalized intersections. Transportation Research Part C 17, 412-427.

29. Liu, Y., Chang, G.L., 2011. n arterial signal optimization model for intersections experiencing queue spillback and lane blockage. *Transportation Research Part C* 19, 130-144.

30. Lo, H.K., 2001. A cell-based traffic control formulation: Strategies and benefits of

dynamic timing plans. *Transportation Science* 35, 148-164.

31. Lo, H.K., Szeto, W.Y., 2002. A cell-based dynamic traffic assignment model: Formulation and properties. *Mathematical and Computer modeling* 35, 849-865.

32. Logghe, S., Immers, L.H., 2008. Multi-class kinematic wave theory of traffic flow. *Transportation Research Part B* 42, 523-541.

33. May, A.D., 1990. *Traffic Flow Fundamentals*. Prentice Hall, Englewood Cliffs.

34. McShane, W.R., Roess, R.P., 1990. *Traffic Engineering*. Prentice Hall, Englewood Cliffs.

35. Michalewicz, Z., 1992. *Genetic Algorithms + Data Structures = Evolution Programs*. Springer, Berlin.

36. Mirchandani, P., Head, L., 2001. real-time traffic signal control system: architecture, algorithms, and analysis. *Transportation Research Part C* 9, 415-432.

37. Mohamed, B.T., Mohamed, S.K., Murali, A., 1999. A two-stage fuzzy logic controller for traffic signals. *Transportation Research Part C* 7, 353-367.

38. Munoz, L., Sun, X., Sun, D., Gomes, G., Horowitz, R., Alvarez, L., 2004. Methodological calibration of the cell transmission model. *Proceedings of the 2004 American Control Conference*, Boston, 798-803.

39. Murat, Y.S., Gedizlioglu, E., 2005. A fuzzy logic multi-phased signal control model for isolated junctions. *Transportation Research Part C* 13, 19-36.

40. Niittymäki, J., 2001. Installation and experiences of field testing a fuzzy logic controller. *European Journal of Operational Research* 131, 273-281.

41. Papageorgiou, M., Papamichail, I., Spiliopoulou, A.D., Lentzakis, A.F., 2008. Real-time merging traffic control with applications to toll plaza and work zone management. *Transportation Research Part C* 16, 535-55.

42. Pappis, C.P., Mamdani, E.H., 1977. A fuzzy logic controller for a traffic junction. *IEEE Transactions on Systems, Man and Cybernetics* 7, 707-717.

43. Pham, V.C., Alam, F., Potgieter, J., Fang, F.C., Xu, W.L., 2011. Integrated fuzzy signal and ramp-metering at a diamond interchange. *Journal of Advanced Transportation*, DIO: 10.1002/atr.167.

44. Richard, P.I., 1956. Shockwaves on the highway. *Operations Research* 4, 42-51.

45. Schmocker, J., Ahuja, S., Bell, M., 2008. Multi-objective signal control of urban junctions-Framework and a London case study. *Transportation Research Part C* 16, 454-470.

46. Smilowitz, K., Daganzo, C., 1999. *Predictability of time-dependent traffic backups and other reproducible traits in experimental highway data*. Working paper UCB-ITS-PWP-99-5, California PATH Program, Institute of Transportation Studies, University of California, Berkeley, CA, USA.

47. Sun, X., Han, L.D., Urbanik, T., 2011. Secondary coordination at closely spaced actuated traffic signals. *Journal of Transportation Engineering* 137, 751-759.

48. Teodorovic, D., 1999. Fuzzy logic systems for transportation engineering: the state of the art. *Transportation Research Part A* 33, 337-364.

49. Waller, S. and Ziliaskopoulos, A., 2001. Stochastic dynamic network design problem. Transportation Research Record 1771, 106-113.

50. Wang, L., Yen, J., 1999. Extracting fuzzy rules for system modeling using a hybrid of genetic algorithms and Kalman filter. *Fuzzy Sets and Systems* 101, 353-362.

51. Wong, C.K., Wong, S.C., Lo, H.K., 2010. A spatial queuing approach to optimize coordinated signal settings to obviate gridlock in adjacent work zones. *Journal of Advanced Transportation* 44, 231-244.

52. Wong, S.C., 1997. Group-based optimisation of signal timing using parallel computing. *Transportation Research Part C* 5, 123-139.

53. Wu, Y.Z., Ho, C.H., 2009. The development of Taiwan arterial traffic-adaptive signal control system and its field test: A Taiwan experience. *Journal of Advanced Transportation* 43, 455-480.

54. Xu, H., Zheng, M., 2009. Impact of Phase Scheme on Development and Performance of a Logic Rule-Based Bus Rapid Transit Signal Priority. *Journal of Transportation Engineering* 135, 953-965.

55. Yao, R., 2012. Sensitivity analysis of optimization models for isolated intersections with short left-turn lanes on approaches. *Journal of Advanced Transportation*, DOI: 10.1002/atr.1185.

56. Zadeh, L., 1973. utline of a new approach to the analysis of complex systems and decision processes. *IEEE Transactions on Systems, Man and Cybernetic* 3, 28-44.

57. Zhang, M., Ritchie, S., Recker, W, 1996. Some general results on the optimal ramp control problem. *Transportation Research Part C* 4, 51-69.

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Thesis: A Multi-Attribute Evaluation Model of Rescue and Evacuation Routes for the Accident in Highway Long Tunnel

B.S. Department of Traffic and Transportation Engineering and Management
Feng Chia University, Taichung, Taiwan (1999/09-2003/06)

RESEARCH EXPERIENCE

Research Assistant National Tung University, Taiwan (2007/09-2012/09)
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AWARDS

Best Student Paper Award: Conference on Traffic Engineering and Intelligent Transportation Systems, 2009.
Best Student Paper Award: Cross-strait Conference on Intelligent Transportation Systems, 2009.

PUBLICATION

Journal

1. Chiou, Y.C. and Huang, Y.F. (2012) "Stepwise genetic fuzzy logic signal control under mixed traffic conditions," *Journal of Advanced Transportation* (SCI) (Accepted)
2. Chiou, Y.C. and Huang, Y.F. (2012) "Genetic fuzzy logic traffic signal control with cell transmission modeling," *Journal of the Chinese Institute of Engineers* (SCI) (Accepted)
3. Chiou, Y.C. Huang, Y.F. and Lin, P.C. (2012) "Optimal variable speed-limited control under abnormal traffic conditions," *Journal of the Chinese Institute of Engineers* (SCI), Vol. 35 pp.299-308
4. 邱裕鈞、王銘德、黃彥斐 (民 100)，「臺灣地區公路客運供給與補貼之區域資源分配差異分析」，**運輸計劃季刊**(TSSCI) 。(已接受)

5. 邱裕鈞、張凱羚、黃彥斐 (民 93)，「公路長隧道事故救援策略之多準則決策模型」，**交通學報**，第四卷第二期，第 93～112 頁。

Conference

1. Chiou, Y.C., Lan, L.W., Huang, Y.F. and Hsieh, C.W. (2011) "Traffic responsive signal control system under mixed traffic conditions," *presented at the 16th Conference of Hong Kong Society for Transportation Studies*, Hong Kong, China, Dec. 17-20.
2. Chiou, Y.C. and Huang, Y.F. (2011) "Stepwise genetic fuzzy logic signal control under mixed traffic conditions," *presented at the International Conference on Advances in Highway Engineering & Transportation Systems & Transport Research Forum 2011*, Colombo, Sri Lanka, July 25-27.
3. Chiou, Y.C. and Huang, Y.F. (2010) "Genetic fuzzy logic traffic signal control with a stepwise learning algorithm," *presented at the 15th Conference of Hong Kong Society for Transportation Studies*, Hong Kong, China, Dec. 11-14.
4. Chiou, Y.C., Lan, L.W., Lin, P.C. and Huang, Y.F. (2009) "Development of optimal variable speed-limit control model," *presented at the 14th Conference of Hong Kong Society for Transportation Studies*, Hong Kong, China, Dec. 10-12.
5. 邱裕鈞、林柏辰、黃彥斐 (民 98)，建立異常交通狀況下之可變速限控制模式，2009 大專院校交通工程與智慧型運輸系統專題論文/創作成果競賽暨研討會，臺灣，臺北，12 月。
6. 邱裕鈞、黃彥斐 (民 98)「基因模糊邏輯號誌控制系統-格位轉換模式之模擬分析」，2009 海峽兩岸智慧型運輸系統學術研討會，臺灣，臺中，5 月。

Research Report

1. 邱裕鈞（2011-2012），「混合車流下之綠色適應性交通號誌控制模式」,國科會專題研究報告(編號：NSC 100-2221-E-009-121)
2. 邱裕鈞（2008-2011），「基因及螞蟻規則探勘模式－以事故分析及事故鑑定為例（I、II&III）」，國科會專題研究報告（編號：NSC 97-2628-E-009-035-MY3）
3. 邱裕鈞（2007-2010），「應用車輛辨識系統提昇起迄旅次矩陣推估之研究（I、II&III）」，國科會專題研究報告（編號：NSC96-2628-E-009-171-MY3）
4. 邱裕鈞（2007-2008），「預測型模糊邏輯匝道儀控系統之建構與驗證（I & II）」，國科會專題研究報告（編號：NSC95-2221-E-009-368-MY2）

5. 邱裕鈞等（2012），「公路公共運輸發展政策推動效益之評估與回饋－運具選擇行為變動之分析及決策支援系統建置(2/2)」，交通部運輸研究所委託。
6. 邱裕鈞（2012），「101 年運輸研究統計資料蒐集及彙編」，交通部運輸研究所委託。
7. 邱裕鈞等（2011），「公路公共運輸發展政策推動效益之評估與回饋－運具選擇行為變動之分析及決策支援系統建置(1/2)」，交通部運輸研究所委託。

8. 邱裕鈞(2011),「100 年運輸研究統計資料蒐集及彙編」,交通部運輸研究所委託。
9. 馮正民、邱裕鈞等(2011),「因應公路客運業市場環境與結構改變政府之輔導轉型策略與管理技術研究」,交通部運輸研究所委託。
10. 馮正民、邱裕鈞等(2010),「前瞻運輸物流管理系統整體發展架構與推動策略規劃」,交通部運輸研究所委託。
11. 馮正民、邱裕鈞等(2009),「強化公路公共運輸政策研析」,交通部運輸研究所委託。
12. 邱裕鈞、鍾政棋(2008~2010),「97-99 年運輸研究統計資料蒐集及彙編」,交通部運輸研究所委託。
13. 邱裕鈞、陳穆臻、鍾政棋(2007),「96 年運輸研究統計資料蒐集及彙編」,交通部運輸研究所委託。
14. 邱裕鈞、艾嘉銘、温傑華(2005~2007),「高速公路局中區工程處交控中心人力委外工作」,國道高速公路局中區工程處委託。
15. 邱裕鈞、鍾政棋、艾嘉銘(2006),「本所運輸統計資料蒐集與整理彙編」,交通部運輸研究所委託研究報告。
16. 李秉乾、楊龍士、邱裕鈞等(2003-2005),「協助彰化縣、台中市改善災害防救計畫」,國家災害防救科技中心委託研究計畫。