# Improving Bus Terminal Operations with Internal Adaptive Traffic Control

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**Abstract:** To accommodate the heavy travel demand in high-density areas, Taipei Bus Station (TBS) is developed as the first multi-level bus terminal in Taipei City. TBS also plays important roles in congestion mitigation, energy conservation and pollutant reduction. Unlike conventional single-level terminals, bus flow interruption while circulating in TBS could significantly impact the service quality and deteriorate environmental condition. Considering time-varying demand and existing Radio Frequency Identification (RFID) monitoring systems, this study constructed an adaptive signal control model combining an artificial neural network (ANN) demand forecasting model to manage bus traffic in TBS. In the case study, the self-retraining demand forecasting algorism is programmed in existing controller/computer to facilitate demand changes. The proposed model has demonstrated itself very efficient in reducing congestion within the terminal.

*Keywords:* multi-level terminal, adaptive traffic control, artificial neural network, self-retraining

## 1. INTRODUCTION

Most public transportation systems, either highway or rail, are prone to various operational problems, including congestion, delays, poor on-time performance, high costs, and deteriorating quality of travel experience. However, there are some cases in which system performance can be elevated with new infrastructure, technology, and/or service and management innovations.

Many studies have focused on location planning of a transit facility adjacent to potential destinations for large numbers of transit passengers. Optimizing the performance of transfer centers such as bus terminals and major train stations is also a popular subject in this field. The transit industry is not exempt from the trend toward increased use of new technologies. Global-positioning-systems (GPS) and other location technologies (e.g. RFID Systems) can be coupled with wireless communication, enabling transit vehicles to be tracked in real-time. These technologies make it possible to control and coordinate transit vehicle movement en-route, enhancing the connectivity between bus lines at transfer terminals.

The Taipei Bus Station (TBS), inaugurated in 2009, is the main terminal and hub for intercity bus services. It is situated at the crossing of two major arterials (Cheng-De Road and Civil Boulevard) in Taipei Metropolitan Area. TBS is a three-level terminal with 39 gates for regular operations and hosts 11 companies serving 40 inter-city express bus routes. Figure 1 shows building structure, bus circulation configuration and RFID detector locations of TBS. There are two exits for buses, the Cheng-De exit and the Civil Boulevard exit, both located on the 3rd floor. TBS had been equipped with a RFID system to monitor the circulation of buses, marking the first application of RFID to a transit terminal. There are more than 200 buses each hour entering TBS during peak periods. Traffic flows interrupting and merging at driveway junctions tend to decrease the operating efficiency, especially at the Cheng-De exit, where significant congestion is often experienced during peak periods. A traffic light has been set to manage flows merging at Cheng-De exit. However, the effect is quite limited due to the fixed timing plan that cannot accommodate time varying bus flows.

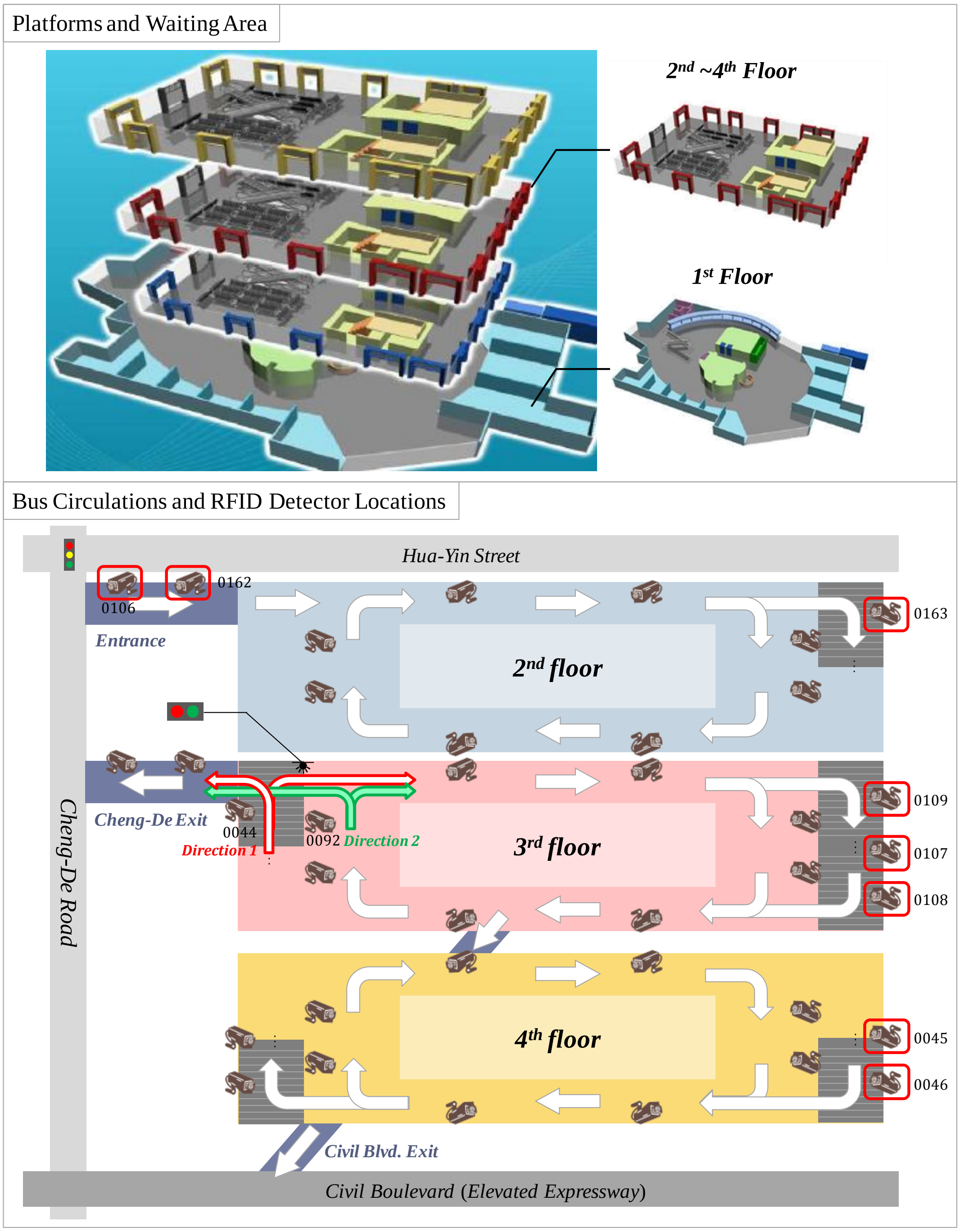


Figure 1. Internal Layout of TBS

Wei *et al.* (2011) proposed an analytical signal control model, a pre-timed approach, to minimize the delay at the Cheng-De exit. This study further improves the signal control strategy for Cheng-De exit enabled by wireless communication and vehicle tracking technologies. The proposed adaptive control method in this paper decides the timing plan using an ANN model calibrated by Wei *et al.* (2013) to forecast the bus flow approaching the target junction. This flow forecasting method is based on traffic information collected at upstream sites selected by circulation analysis in TBS. Figure 2 shows the structure of adaptive signal control model for TBS. The proposed model is calibrated and tested with real-world data collected from RFID readers.

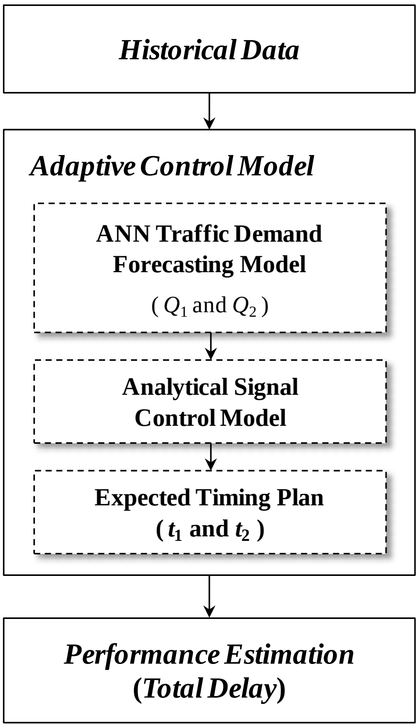


Figure 2. Adaptive Signal Control Model Structure

The remainder of this paper is divided into five sections. Section 2 presents a review of the literature on improvements of bus terminal operations in traditional and multi-level bus terminals, and previous studies of TBS on signal control methods. In Section 3, the architecture of the adaptive control model for TBS and model performance assessment is presented. Section 4 provides a self-retraining structure to improve model performance continuously and programs a preliminary testing. Section 5 presents the sensitivity analysis. Finally, Section 6 summarizes findings and suggests subjects for further research.

## 2. BACKGROUND AND LITERATURE REVIEW

There are many ways to improve transit service quality, including reduced crowding, increased service frequency, nicer waiting areas, and better user information (Litman, 2008). Traditional transport evaluation methods tend to focus on cost-effective transit improvement strategies, resulting in under-investment in transit service quality improvements. Such circumstances in turn make transit less attractive compared to automobile travel. Service quality improvements that reduce the unit cost of travel time provide benefits that are comparable to speed improvement in reducing total travel time.

Another way to improve transit service quality is providing transit users with real-time, reliable information at bus stops and terminals (e.g., signs, printed and posted schedules, conventional and automated telephone services, transit websites, changeable signs or monitors at stations and stops, and announcements). New technologies for predicting next vehicle arrival time at a particular destination have been articulated with real-time information provided to transit users.

Conventional planning practices tend to solve problems and focus on service quality issues in single-level bus terminals. However, transit systems must handle greater traffic loads as populations in urban area continue to increase, particularly in central districts. Multi-level transportation terminals represent a solution to this problem, and have become a trend in high-density areas. Thus, improving multi-level terminal operational performance is a critical task in major cities around the world.

Traffic control systems evolved through several generations. The first generation of such systems has been based on historical traffic data. The second generation took advantage of detectors, which enabled the collection of real-time traffic data, in order to re-adjust and select traffic signalization programs. The third generation provides the ability to forecast traffic conditions, in order to have traffic signalization programs and strategies pre-computed and applied at the most appropriate time frame for the optimal control of the current traffic conditions (Mitsakis, 2011).

Significant delay occurs during peak periods at the Cheng-De exit of TBS. Taking into consideration TBS geographic constraints and operational characteristics, Wei *et al.* (2011) optimized signal timing to reduce the delay. The proposed model clearly indicates the relationships among flow rate, capacity, discharge time, and delay. The delay is sensitive to discharge time allocated for each direction, especially at peak periods with high traffic volumes. Results show that performance of the proposed model is promising. Reduction of delays by 22%-38% was observed at different times of the day.

Adaptive signal control, the latest generation of dynamic signal control methods, refers to any signal control strategy that can adjust signal operations in response to fluctuating traffic demand and achieve greater efficiency than pre-timed systems in stops, delays, and emissions. Among the adaptive control strategies, the Sydney Coordinated Adaptive Traffic System (SCATS) and Split, Cycle and Offset Optimization Technique (SCOOT) models have been applied in several cities to achieve transportation system effectiveness and efficiency. However, these two models are designed mainly for unban street systems and configuration is too complex to deploy in TBS.

Different techniques have been considered to enhance traffic control performance and to minimize traffic delay. Applications with fuzzy logic in controlling traffic signals have been used since the 1970s. The strength of fuzzy logic lies in its capability of simulating the decision-making process of a human, a process that is often difficult to define with traditional mathematical methods.

Zaied and Othman (2011) proposed a system to change green light duration involving fuzzy factors and tested it using real data collected from signalized intersections. It provided good results compared to a pre-timed control strategy when considering heavy traffic volumes due to reducing the unused green time and accelerating the phase’s sequences. Keyarsalan and Montazer (2011) discovered that traffic light control domain using a fuzzy ontology made lower average delay time concerning weather and congestion conditions when applied to isolated intersections. Modeling knowledge of this domain helps traffic agents and application examples manage traffic efficiently regarding real-time conditions.

It is known that the human brain and nervous systems have enormous capabilities of pattern recognition in sensory perceptions. ANNs are models used to emulate the human pattern recognition function through a similar parallel processing structure of multiple inputs (Jain *et al.*, 1997). After studied for decades, the improved BP neural network provides a new and feasible thought to predict. The main idea of the BP neural network is as follows: For the given learning samples, the network inputs are made to be equal to the samples' outputs. Then the weight is revised by the error between the practical outputs and the learning samples' outputs and the network output values and the samples' output values are made to be close as possible (Wang *et al.*, 2007).

Hwang (1994) applied ANN to forecast vehicles turning ratio at each intersection and satisfactory performance was obtained for a practical urban network case. Hsu (2003) constructed a traffic control system possessing the capabilities of ANN and demonstrated the flexibility of ANN to fulfill the function of traffic adaptive signal control systems.

To improve operational efficiency of TBS, Wei *et al.* (2013) shortened the control time intervals and developed an ANN traffic forecasting model with an embedded RFID monitoring system throughout TBS. It is found that separate forecasting models for peak hours and non-peak hours would be desirable for both directions approaching Cheng-De exit. The best ANN model for Direction 1 uses flow rates as inputs on all upward slopes, computing by gradually learning rate training method with only 1 hidden node. For Direction 2, the optimal ANN model requires flow rate square root forecasting by 9 detecting data (8 readers embedded on each upward slope and 1 at Direction 2) computing by scaled conjugate gradient training function with 5 hidden nodes.

The timing functions and ANN forecasting models synthesize the detecting data to identify current and short-term future flow conditions. This makes it possible to propose an adaptive signal control model that uses the identified flow conditions to make intelligent signal timing decisions.

## 3. ADAPTIVE CONTORL MODEL DEVELOPMENT

The proposed adaptive signal control model (Figure 2) combines an analytical signal timing model and demand responsive mechanism, the ANN forecasting model. According to real-time up-stream detecting data provided by RFID systems, the ANN model predicts flow rates in next time period for Directions 1 and 2 respectively. Then, the optimized timing plan is computed by timing functions. In this case, Direction 1 is defined as the flows coming from $4^{th}$ floor; Direction 2 is flows circulating on $3^{rd}$ floor (please refer to Figure 1). Section 3.1 and Section 3.2 introduce the advanced analytical signal model and ANN forecasting model, respectively. In Section 3.3, the architecture of adaptive control model and performance are presented.

### 3.1 Analytical Signal Timing Model

The model proposed originally by Wei *et al.* (2011) shows the relationship among flow rates, capacity, queue length, and delay (Figure 3). The optimal discharge timing can be derived from the cyclical queuing processes resulting from predicted flows in different directions under ideal situation. The signal timing equations are expressed as Eqs. (1) and (2).

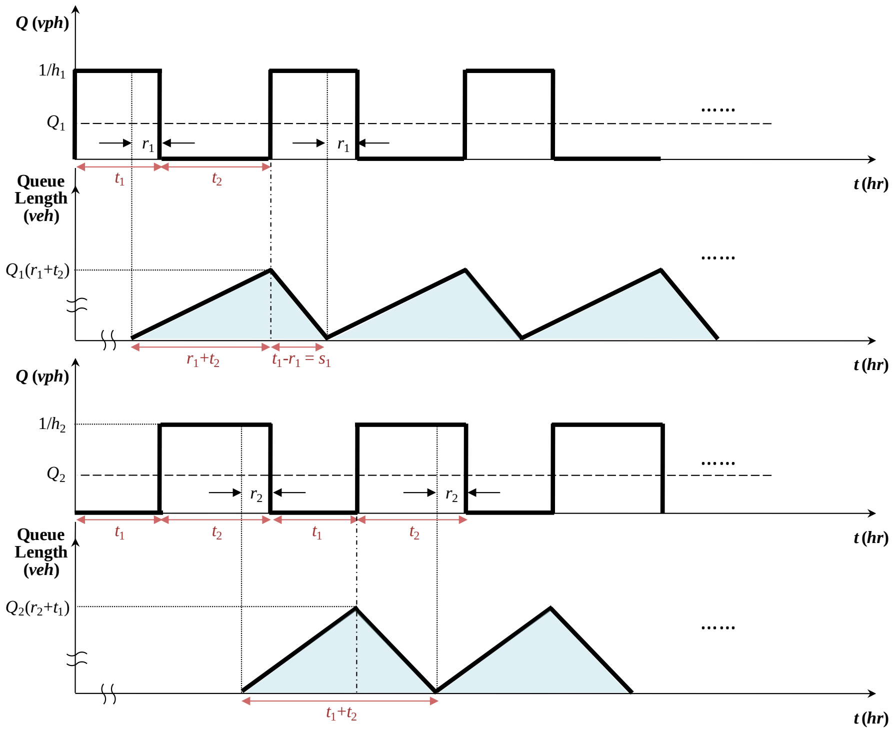


Figure 3. Flow Rate and Queue Length over Time (under saturated)

$$t_{1n} = \left[\frac{Q_{1n}\times C_2\times r_2 + C_1\times r_1(C_2 - Q_{2n})}{C_1\times C_2 - Q_{1n}\times C_2 - Q_{2n}\times C_1} + t_r\right]\times 3600 \le (L_2/Q_{2n}(l+d)) - r_2 \tag{1}$$

$$t_{2n} = \left[\frac{Q_{2n}\times C_1\times r_1 + C_2\times r_2(C_1 - Q_{1n})}{C_1\times C_2 - Q_{1n}\times C_2 - Q_{2n}\times C_1} + t_r\right]\times 3600 \le (L_1/Q_{1n}(l+d)) - r_1 \tag{2}$$

where,

$t_{dn}$: Discharge time of Direction *d* at time interval *n* (*sec.*);

$Q_{dn}$: Flow rate of Direction *d* at time interval *n* (*vehicles per hour*);

$C_d = 1/h_d$: Capacity of Direction *d* (*vph*), derived by inverse of minimum discharge headway of Direction *d* ($h_d$, *hr.*);

$r_d = K_d/s_d$: Clearance time of Direction *d* (*hr.*), derived by distance of passing through intersection ($K_d$, *km*) divided by average discharge speed ($s_d$, *kph*);

$t_r$: Average driver response time (*hr.*);

$L_d$: Maximum allowable queue length of Direction *d* (*m*);

*l*: Average vehicle length (*m*);

*d*: Average space gap between vehicles (*m*).

In reality, residual queue often occurs when demand exceeds the capacity or discharge time is not enough to clear the waiting vehicles as indicated in Figure 4. This situation is particularly worth noting if the signal timing design is based on shorter time intervals in which flow fluctuation may cause exceeding demand and resulting in queues. Given the optimal signal timings estimated by Eqs. (1) and (2), the residual queue should be considered when cumulative demand is larger than service capacity as shown in Figure 5.

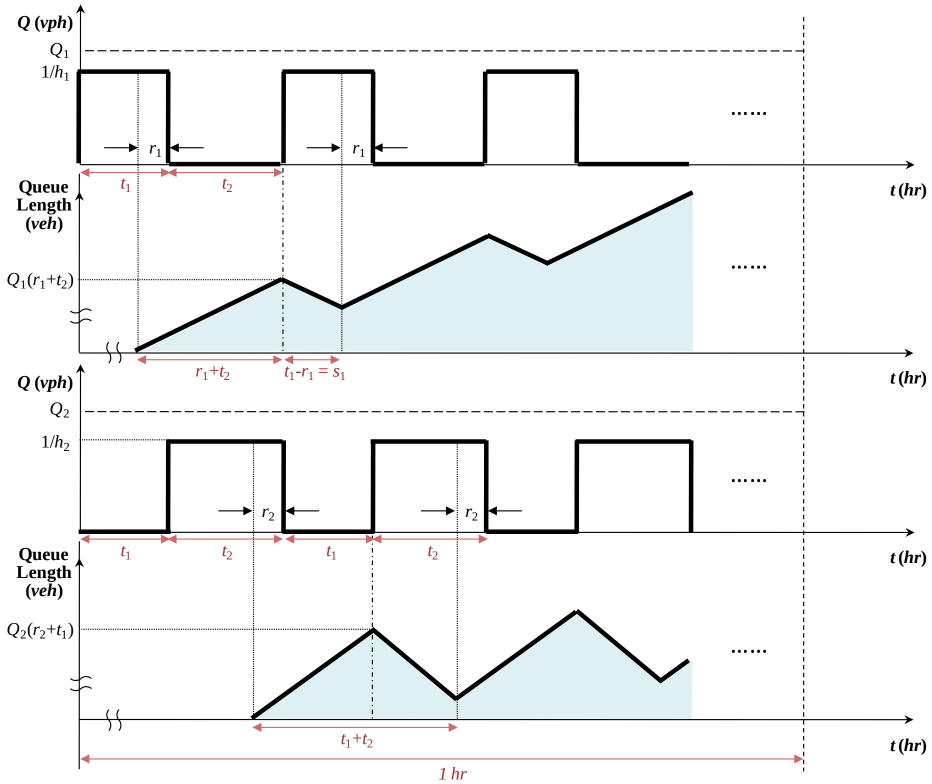


Figure 4. Flow Rate and Queue Length over Time (over saturated)

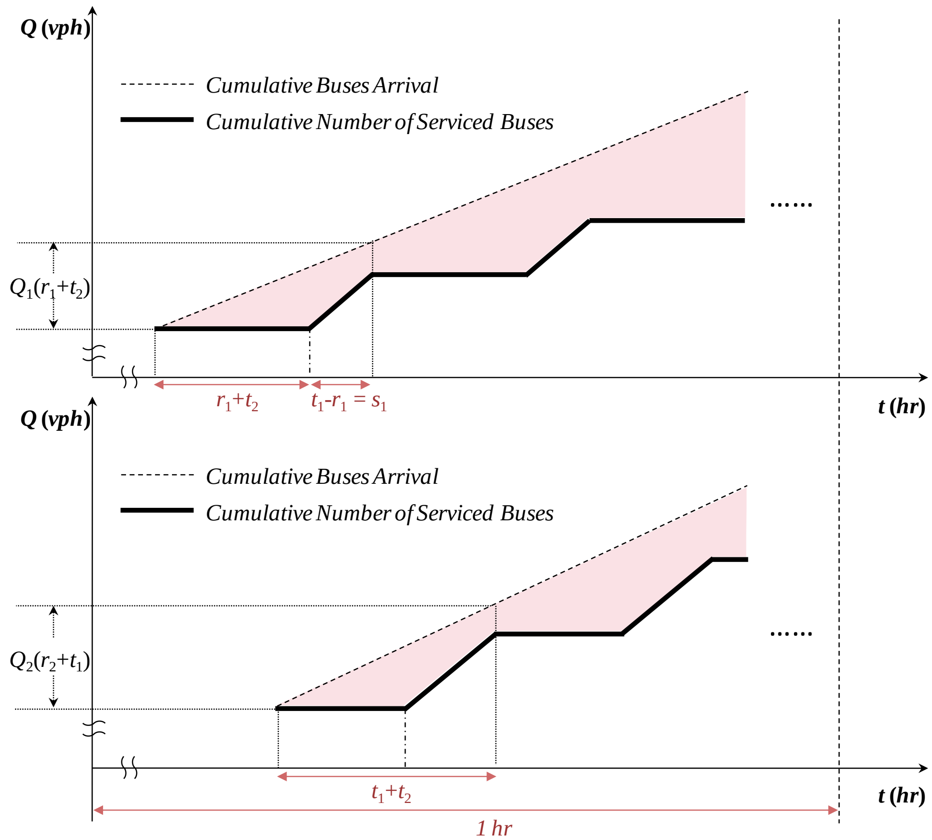


Figure 5. Cumulative Demand vs. Served Buses (over saturated)

For estimating signal control delay in any situations, delay functions for Directions 1 and 2 can be written as Eqs. (3) and (4), respectively.

$$D_{1n} = \left[\frac{1}{2} Q_{1n}(r_1 + t_{2n})^2\right] + \left[\frac{1}{2}\big((Q_{1n}(r_1 + t_{2n}) + MAX(Q_{1n}(r_1 + t_{2n}) - C_1(t_{1n} - r_1), 0))\big)(t_{1n} - r_1)\right]$$
$$+[(MAX(Q_{1n}(r_1 + t_{2n}) - C_1(t_{1n} - r_1), 0))(t_{1n} + t_{2n})(i - 1)] \quad (3)$$

$$D_{2n} = \left[\frac{1}{2} Q_{2n}(r_2 + t_{1n})^2\right] + \left[\frac{1}{2}\big((Q_{2n}(r_2 + t_{1n}) + MAX(Q_{2n}(r_2 + t_{1n}) - C_2(t_{2n} - r_2), 0))\big)(t_{2n} - r_2)\right]$$
$$+[(MAX(Q_{2n}(r_2 + t_{1n}) - C_2(t_{2n} - r_2), 0))(t_{1n} + t_{2n})(i - 1)] \quad (4)$$

where,

$D_{dn}$: Hourly delay of Direction $d$ at time interval $n$ (*vehicle-seconds per hour*, *vsph*);

$i$: Serial number of cycle in one hour (*times*);

### 3.2 ANN Bus Flow Forecasting Model

Applying the forecasting models developed by Wei *et al.* (2013), the ANN forecasting model for Direction 1 requires flow rates detected on each upward slope as input variables. The gradual learning rate training method with only 1 hidden node is assessed as the most efficient construct. For Direction 2, the flow rate is forecasted in square root while the input layer consists of 9 detecting data (8 RFID readers embedded on each upward slope and one near the Cheng-De exit on Direction 2). The corresponding ANN model is based on scaled conjugate gradient training function with 5 hidden nodes. Evaluation results show that separate forecasting models for peak hours and non-peak hours are desirable for both directions. Table 1 summarizes the parameters of forecasting modules and performances. The time period for iterative forecasting is set as 10 minutes, the average in-terminal time (including routing time and on-board/off-board time), for reasonably responding to alternates of flow rate. The average forecasting error of each direction is less than 3.5 buses for a 10-minute updating interval.

Table 1. ANN Traffic Forecasting Models and Performance

| Direct-ion | No. of Inputs | No. of Hidden Nodes | Training Method | Learn Rate | LR decre-ment | Data | RMSE | MAPE | Ave. Error (buses) |
|---|---|---|---|---|---|---|---|---|---|
| Dir 1 | 3 | 1 | Gradual Learning Rate | 0.05 | 0.7 | Peak | 0.14 | 0.36 | 1.93 |
| | | | | | | Non-Peak | 0.13 | 0.41 | 1.60 |
| Dir 2 | 9 | 5 | Scaled Conjugate Gradient | - | - | Peak | 0.09 | 0.12 | 3.49 |
| | | | | | | Non-Peak | 0.11 | 0.21 | 2.34 |

Note: RMSE (Root Mean Square Error) = $\sqrt{[\sum_{n=1}^{N}(\widehat{z_n} - z_n)^2]/N}$;
MAPE (Mean Absolute Percentage Error) = $\frac{1}{N}|\sum_{n=1}^{N}[(\widehat{z_n} - z_n)/z_n]| \times 100\%$.

### 3.3 Adaptive Control Model Testing

As Figure 2 shows, the adaptive signal control model for the Cheng-De exit was developed using the ANN traffic forecasting model to predict the coming traffic flows. A time-dependent signal timing function determines the optimal cycle length and green time in each 10-minute interval based on the predicted flow rates. With the ANN forecasting model, the discharge times are estimated and deployed with less congestion responding to variable flow rates over time.

Table 2 shows the performance comparison of current, pre-timed, and adaptive control methods. In this case, with operators' observations and field investigation, the minimum discharge headways ($h_1$ and $h_2$) are both 5 sec.; clearance times ($r_1$ and $r_2$) are 12 sec. and 11 sec., respectively; average driver response time is 1.3 sec.; maximum queue lengths ($L_1$ and $L_2$) are 70 meters and 60 meters; average vehicle length is 12 meters; the average space gap between vehicles is one meter.

The current green time duration for Direction 1 at the target intersection is 20 seconds fixed, and 40 seconds fixed for Direction 2. The pre-set timing plan in this study is chosen according to average time-of-day flow rates during one month. Figures under the "Ideal" column are the minimum hourly delays while discharge times are estimated by real flow rates.

By performing the proposed adaptive control method, the lowest average hourly delay was achievable. The results are very promising, which can reduce 51% and 26% delay for traffic on Directions 1 and 2, respectively, compared to the current control method. The advantage of adaptive control model may be more significant on extreme occasions, ex. long holiday period.

Table 2. Model Performance Results

| Period | Direction | Average Hourly Delay (*unit: vehicle-second per hour*, *vsph*) | | | |
|---|---|---|---|---|---|
| | | Ideal* | Current | Pre-timed | Adaptive |
| Peak | 1 | 589 | 1,205 | 599 | 592 |
| | 2 | 1,234 | 1,691 | 1,282 | 1,259 |
| Non-peak | 1 | 336 | 732 | 343 | 338 |
| | 2 | 536 | 753 | 557 | 557 |

* The minimum hourly total delay while discharge times are estimated by real flow rates and the optimal timing plans.

Wei *et al*. (2011) discovered that the discharge time for Direction 1 during peak hours is 17-18 seconds and 19-20 seconds for Direction 2. This indicates that the current timing plan operates with low efficiency, especially in Direction 1 where the average waiting time is doubled. As a main intercity bus terminal at the heart of a large city, TBS must maintain high efficiency all the time. This necessitates an adaptive control method for Cheng-De exit, which is the most congested node during peak hours in the terminal

## 4. PRELIMINARY TEST OF SELF-RETRAINING STRUCTURE

### 4.1 Self-Retraining Algorism and Operating Procedure

The proposed adaptive signal control model includes an on-line self-retraining mechanism to avoid RFID malfunction and flow forecasting error. It also facilitates the needs to renew signal timing plans when conducting alternation of daily scheduling of routes and platforms in the future. Figure 6 shows the on-line operating procedure that accommodates the proposed self-retraining feature. The control method includes a pre-timed timing plan and real-time adaptive timing plan estimated with forecasted flow rates. The steps are explained as follows:

1) Considering system computational load and the possibility of adaptive control system breaking down, control at the Cheng-De exit is set default as the pre-timed mode. As the ANN forecasting model monitoring the variation in the flow rates, the optimal timing plan will be computed and applied basing on the flow rates. The more details are as below.
2) Prior to evaluation, the ANN forecasting model and database of pre-set plans shall be well prepared and installed to the current control systems in TBS.
3) As the ANN model receives the flow rates of the previous time interval ($T = t - 1$), forecasting the flow rates merging at the junction next to Cheng-De exit will be activated for the target time interval ($T = t$).
4) Based on the forecasted flow rates, an adaptive timing plan ($B_T$) is optimized by the proposed adaptive control model. The adaptive phasing plan will be executed at time interval $t$ if it differs from the pre-set timing plan; otherwise, the pre-timed plan ($A_T$) is applied.
5) While performing the adaptive signal plan at time interval $t$, record the actual bus flow rates.
6) Before the end of interval $t$, evaluate control performance (i.e. hourly delay) of the prevailing timing plan (either pre-timed plan $A_T$ or adaptive timing plan $B_T$), and compare to ideal timing plan based on actual arrival flow rates at Cheng-De exit. If the difference is greater than allowable tolerance ($p$%), the self-retraining mechanism will commence.
7) Tolerance is the minimum increment of hourly delay that determines whether ANN model retraining (i.e., weights recalibration) is required. Verification should be conducted for both Directions 1 and 2 for each time interval.
8) If the ANN model is retrained, the weights of the ANN model are revised according to the prediction error. Then, the retrained model is used to predict the flow rates of the next time interval ($T = t + 1$). Alternatively, if a timing plan is applied and performs well, the adaptive timing plan will replace the pre-timed plan at time $t$. That is the advantage of self-retraining for route-platform reassignment.
9) Repeat Steps 3 to 8.

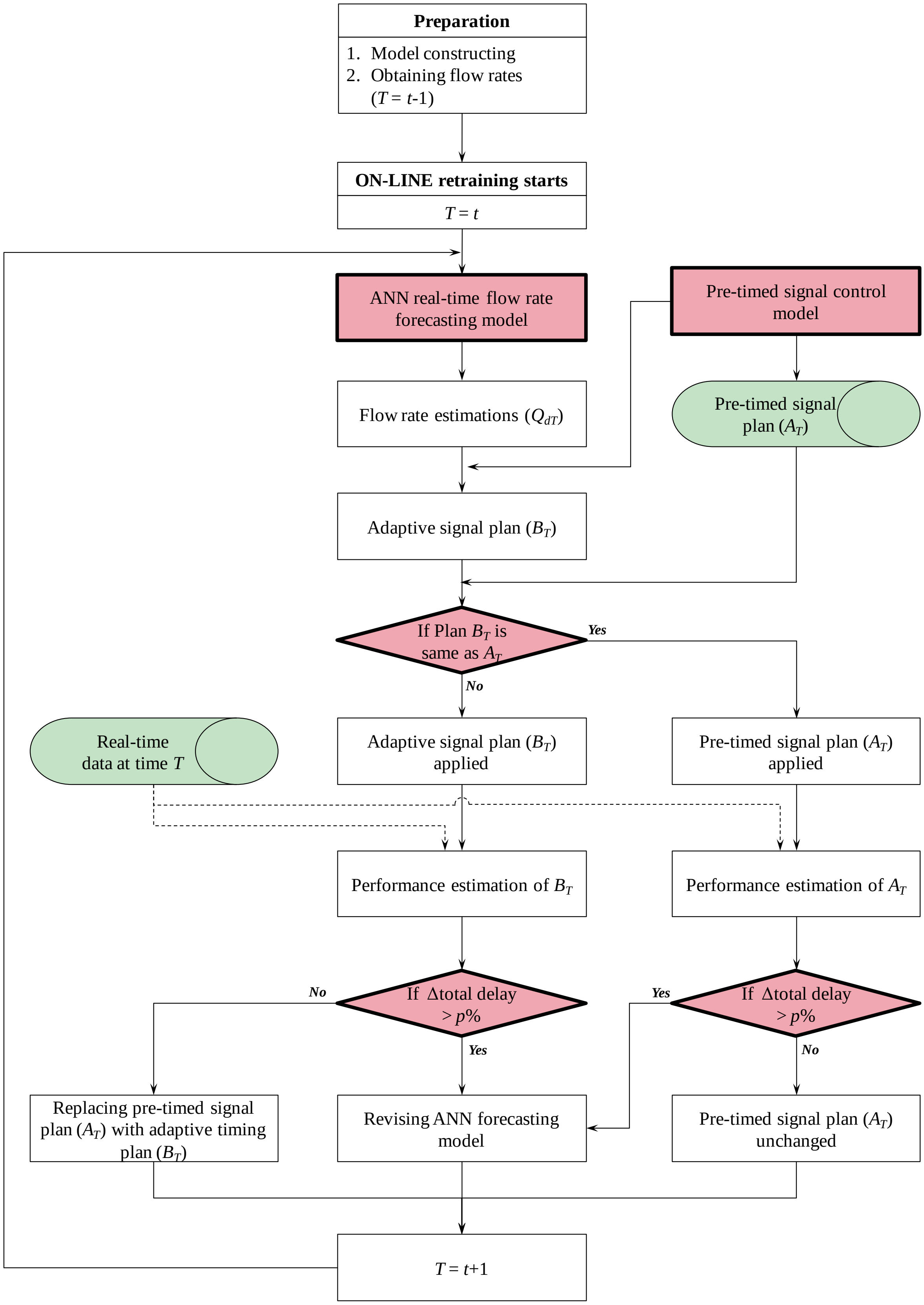


Figure 6. On-Line Operating Procedure

The preliminary test of the proposed procedures was conducted off-line using data extracted from RFID database for a whole week, 2012.04.15 00:00 (Sunday) - 2012.04.21. 23:59 (Saturday). Excluding the last time interval, the sample size for pre-testing was 1,007. To facilitate the test, the model retraining function adopted a fixed learning rate, and was programmed using Visual Basic for Applications (VBA). This study then compares several learning rates (i.e., 0.8, 0.5, 0.1, 0.05, and 0.01) to find the optimal learning rate for future practical applications.

The tolerance of retraining is the difference in total hourly delay between the estimated timing plan and the ideal timing plan. If the difference between the ideal total hourly delay and estimated delay is larger than $p$%, as in Eq. (5), the ANN forecasting model needs adjustment. The total hourly delays are summations of Eq. (3) and (4) computed for each timing plan.

$$\Delta\, Total\ delay = \left|\frac{(Ideally\ total\ hourly\ delay) - (Estimated\ total\ hourly\ delay)}{(Ideally\ total\ hourly\ delay)}\right| > p\% \tag{5}$$

Tolerance $p$ may be determined by verifying the relationship between error of combined flow rate and total hourly delay increment. Figure 7 shows the total hourly delay increment versus error of combination hourly flow rate (the total hourly flow rates merging to Cheng-De exit) under various traffic volumes. The delay curve increases exponentially as the error increases. A higher flow rate leads to a greater delay increment ratio. As Figure 7 depicts, this study uses $p$ = 5% to facilitate precise calibration of ANN models. To examine the impact of $p$ on signal control efficiency, different $p$ values are tested in Section 5.

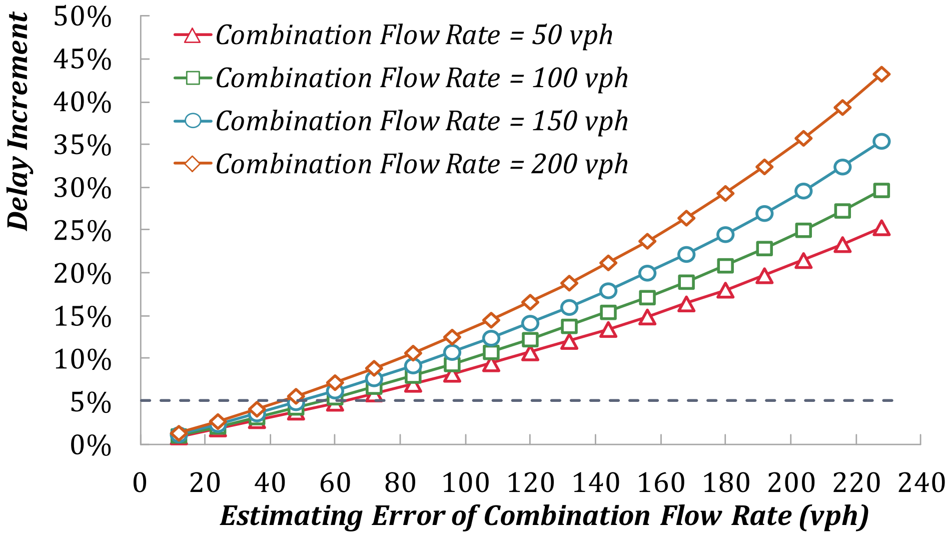

Figure 7. Delay Increment vs. Estimating Error of Combination Hourly Flow Rate

### 4.2 Model Performance

Table 3 presents the performance comparison of various control methods, including fixed ANN model without retraining. Adaptive signal control with fixed ANN model improves the control efficiency, achieving a 34.7% delay reduction in contrast to the current control. The method performs even better with retrained ANN models. When various levels of learning rate are applied, additional 2%-5% delay reduction is attained comparing to the pre-timed control method. It is interesting to note that as the learning rate increases, the hourly delay of

Direction 1 increases, whereas Direction 2 decreases. The minimum total delay is found for the ANN model with a learning rate equal to 0.1.

Table 3. Model Performance of On-Line Preliminary Testing

| Index | | Current | Ideal | Pre-timed | Fixed ANN Model | Retraining ANN Model | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | LR=0.8 | LR=0.5 | LR=0.1 | LR=0.05 | LR=0.01 |
| Avg Hourly Delay | Dir 1 | 1,117 | 554 | 559 | 495 | 572 | 567 | 538 | 516 | 505 |
| | Dir 2 | 1,440 | 1,055 | 1,153 | 1,176 | 1,052 | 1,079 | 1,083 | 1,130 | 1,153 |
| | Total | 2,557 | 1,609 | 1,712 | 1,671 | 1,624 | 1,646 | 1,621 | 1,646 | 1,658 |
| Reduction (%) | | - | 37.1 | 33.1 | 34.7 | 36.5 | 35.6 | 36.6 | 35.6 | 35.2 |

## 5. SENSITIVITY ANALYSIS

Table 4 shows the model performance with respect to the signal timing adopted and the resulting hourly delay under different tolerances for non-peak hours while peak hours are set as 0.05 constantly. Relaxing the tolerance for non-peak periods significantly reduces retraining desired, but slightly increases the total hourly delay. In other words, loosening the retraining threshold can reduce the computational burden of the forecasting model, while avoiding a significant increase in total delay.

The sensitivity analysis in this study shows that the On-Line self-retraining tolerance for peak periods should be set at 0.05 and 0.25 for non-peak periods.

Table 4. Sensitivity Analysis of Tolerance for Non-peak Hours

| Index | | | Retraining ANN Model | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | $p$=0.05 | $p$=0.10 | $p$=0.15 | $p$=0.20 | $p$=0.25 | $p$=0.30 |
| Dir 1 | Times of $B_T$ applied | Peak | 343 | 343 | 343 | 343 | 343 | 343 |
| | | Non-peak | 161 | 180 | 170 | 163 | 176 | 265 |
| | Times of $A_T$ applied | Peak | 164 | 164 | 164 | 164 | 164 | 164 |
| | | Non-peak | 339 | 320 | 330 | 337 | 324 | 235 |
| Dir 2 | Times of $B_T$ applied | Peak | 484 | 484 | 484 | 484 | 484 | 484 |
| | | Non-peak | 363 | 381 | 400 | 410 | 412 | 412 |
| | Times of $A_T$ applied | Peak | 23 | 23 | 23 | 23 | 23 | 23 |
| | | Non-peak | 137 | 119 | 100 | 90 | 88 | 88 |
| Times of retraining | | Peak | 210 | 210 | 210 | 210 | 210 | 210 |
| | | Non-peak | 97 | 70 | 57 | 48 | 39 | 16 |
| Overall Average Hourly Delay | | Dir 1 | 538 | 537 | 536 | 533 | 532 | 532 |
| | | Dir 2 | 1,083 | 1,090 | 1,098 | 1,096 | 1,094 | 1,102 |
| | | Total | 1,621 | 1,628 | 1,634 | 1,628 | 1,626 | 1,634 |

## 6. CONCLUSIONS

Transit systems are strategic solutions to the problem of heavy traffic in high-density areas, and more importantly, energy conservation and pollution reduction. Multi-level terminals are becoming the main terminal structures for cities with high population density (e.g. Taipei, Taiwan and Beijing in mainland China).

Unlike a single-level terminal, flow interruption is a critical operational issue in TBS. This paper presents a case study to apply the proposed adaptive signal control model for managing bus traffic within a multi-level bus terminal. The adaptive control model optimizes signal timings subject to forecasted bus flow with an ANN model. Results indicate that the adaptive control model improves operational efficiency without requiring additional equipments.

This study devises, assesses, and tests a self-retraining method to tackle such potential issues as RFID malfunction, forecasting error, and daily scheduling alternation of routes and platforms. One-week data were applied to appraise the model performance. Results show that varying the timing plan dependent on forecasted demand may yield a 34.7%-36.6% decrease in hourly delay, compared to that of current fixed timing plan. Given the adaptive signal control methods with appropriate learning rates, additional 2%-5% delay reduction may be expected.

To loosen the retraining threshold and computing loading for non-peak hours with fewer traffic demands, this study tests several tolerance values for non-peak hours operations. Results show that relaxing the retraining threshold can decrease the burden of re-computing weights of ANN models with fairly minor delay increase (only around 1%). The suggested self-retraining tolerance for peak and non-peak periods are 0.05 and 0.25, respectively.

There is one recommendation to further study. Cheng-De Road is a major arterial in Taipei City, and Hua-Yin/Cheng-De intersection is near to Cheng-De exit on ground level. A coordinating timing plan for these two intersections is necessary to avoid traffic spill back to TBS.

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