Transfer demand prediction for timed transfer coordination in public transport operational control: Transfer demand prediction for timed transfer coordination

Article *in* Journal of advanced transportation · January 2017

DOI: 10.1002/atr.1440

Minh Le Kieu
University of Auckland

Ashish Bhaskar
Queensland University of Technology

Paulo E. M. de Almeida
Centro Federal de Educação Tecnológica de Minas Gerais

Nasser R. Sabar
La Trobe University

Transfer demand prediction for timed transfer coordination in public transport operational control

Le Minh Kieu*[1], Ashish Bhaskar[1], Paulo E. M. Almeida[2] and Edward Chung[1]

*Corresponding author, email: leminh.kieu@qut.edu.au

[1]Smart Transport Research Centre, Queensland University of Technology, Australia

[2]Centro Federal de Educação Tecnológica de Minas Gerais - CEFET-MG, Belo Horizonte, Brazil

Abstract

Timed transfer coordination in public transit reduces passenger transfer time by providing seamless interconnected transfers. The problem arises when a Receiving Vehicle (RV) arrives first to the transfer stop than a Feeding Vehicle (FV) that carries transferring passengers. Timed transfer coordination in operational control dynamically decides if RV is held at the transfer stop to allow transfers, or departs as scheduled. While transfer demand is essential for implementing timed transfer coordination, this variable is generally not available in public transit due to the lack of passenger transfer plan. The problem of acquiring this variable in real-time has also received scant attention in the literature.

This paper proposes a new method to dynamically predict the transfer demand. We anticipate the transferring probability from each individual passenger by examining their historical travel itineraries. Three different types of models (simple analytical model; statistical model; and computation intelligence model) are developed to forecast the number of transferring passengers. Numerical experiments using observed Automatic Vehicle Location and Automatic Fare Collection data from South East Queensland, Australia show the accuracy and applicability of the proposed models in timed transfer coordination.

Introduction

A seamless interconnected transit system is essentially important to attract ridership. Transfer time is usually perceived as time lost for passengers [1]. Compared with private transport as almost a door-to-door service, a poorly coordinated transfer is one of the decisive factors to discourage people from switching to public transport. Conversely, synchronised timetable and seamless coordination between transit trips are much desired by passengers and could significantly enhance the transit quality of service.

The idea of timed transfer coordination in transit operation control is similar to the successful "hub-and-spoke" system in air transportation. Where, if the incoming flight has been delayed for a certain amount of time, air controller may delay an out coming flight to allow passengers transfer in real-time. The successful of transfer coordination in air transportation highly depends on three principal variables [2]: (1) the delay of the incoming flight; (2) the number of transferring passengers; and (3) the frequency of the outgoing flight. While it is more obvious in air transportation to perform a timed transfer coordination strategy because the number of transferring passengers is known and flights generally are less frequent, similar approaches could also be applied to public transport at low frequency service if transfer demand is predictable. Timed transfer coordination in operational control holds a Receiving Vehicle (RV) in real-time to wait for an incoming Feeding Vehicle (FV) to allow passenger transfers. However, transit operators will need to compare the costs induced by the transfer coordination decision to both transferring and non-transferring passengers to balance the trade-off between the cost of vehicle holding and missed connection under certain number of transferring passengers.

Literature provides some insights into the timed transfer coordination problem in operational control of public transport [2-7]. Although being one of the most important variables in timed transfer coordination, transfer demand is generally not available in real-time and has received scant attention in literature. Most of the existing timed transfer coordination studies assume a transfer demand [4-7] or briefly estimate it using a demand fraction [2, 3], without rigorous examinations of dynamic transfer demand prediction. It is not possible to estimate the cost induced by transfer coordination to transferring and non-transferring passengers if the transfer demand is unknown.

This paper contributes toward timed transfer coordination in operational control by proposing a new method to predict the transfer demand in real-time. The transfer demand is predicted using the knowledge of individual travel pattern: how each passenger makes transfer in historical travel itineraries. Because of the need for continuous observation of travel behaviour, Smart Card based Automatic Fare Collection (AFC) data is exploited in this study. Numerical experiments using observed data show the effectiveness and applicability of the transfer demand prediction model in timed transfer coordination. The contributions of this paper are twofold: (1) to propose a new method to predict number of transferring passenger in real-time, and (2) to show that the quality of transfer demand prediction affects the effectiveness of timed transfer coordination.

The remaining of this paper is organised as follows. After the literature review of existing advances in timed transfer coordination and travel pattern analysis, a methodology section describes the prediction models of transfer demand. Finally, a numerical experiment shows the sensitivity of transfer demand prediction in timed transfer coordination strategies.

Literature review

Timed transfer coordination in operational control

Timed transfer coordination in operational control is a real-time problem involving two transit vehicles of different routes, where passengers from a FV transfer to a RV. The problem arises when RV arrives at the transfer stop before the arrival of FV. It is then broken down to a binary problem of whether the RV should wait for the coming FV, so that passengers can make transfers, or depart the transfer stop as scheduled.

The primary idea of timed transfer coordination in operational control is to predict the arrival time of FV, the non-transfer demand in RV and transfer demand (from FV to RV) to decide if RV should be held for passenger interchange. The idea is similar to the “hub-and-spoke” system at some major connecting airports, where air controller may delay an outcoming flight to allow passengers transfer in case their incoming flight has been delayed for a certain amount of time. The proliferation of advanced data collection systems such as Automatic Vehicle Location (AVL) and AFC has led to the emerging interest in applying similar timed transfer coordination system in public transit. Dessouky *et al.* [2] showed that the presence of real-time AVL data enhanced the performance of timed transfer coordination, otherwise RV might have to delay up to the predetermined holding time without a successful transfer coordination. Dessouky *et al.* [3] followed the same approach as in Dessouky *et al.* [2], but also described the predictions of arrival time, number of transferring and boarding passengers. The authors again concluded that the strategy with most data available would perform best in reducing passenger waiting time. Chowdhury and Chien [5] developed a model for dynamic dispatching of vehicle for maximising transfer opportunities. A cost function consisted of the cost for holding vehicle, delay cost and passenger missed connection cost is minimised. The authors showed that dynamic vehicle dispatching noticeably enhanced the transfer efficiency and reduced total cost. Chung and Shalaby [4] balanced a combined cost function of transfer time, in-vehicle passenger waiting time and downstream passenger waiting time between transferring and non-transferring passengers. The author also emphasised that timed transfer coordination was essential to maintain coordinated transfer due to unexpected delays of transit vehicles. Ting and Schonfeld [6] formulated a heuristic algorithm to optimise the holding time of RV to wait for an incoming FV at a multi-hub transit network. Yu *et al.* [7] proposed a Support Vector Machine model to predict FV's arrival time and elastic time to minimise the total waiting time of passengers at the transfer and downstream stops. A numerical test showed that the proposed dynamic vehicle dispatching strategy could reduce passenger waiting time.

Prediction of transfer demand

The transfer demand is one of the most important factors in these existing on-line transfer coordination cost functions [2, 5]. The transfer demand reveals the time cost to transferring and non-transferring passengers. The transfer demand is generally assumed known or estimated in timed transfer coordination model using an assumption of the transferring fraction. Dessouky *et al.* [2] assumed an equal probability of transferring to all given bus lines at transfer stops. Dessouky *et al.* [3] and Yu *et al.* [7] proposed a simple analytical model to predict the number of transferring passengers by assuming a fraction of transferring passenger. Many other studies such as Chowdhury & Chien [5], Chung & Shalaby [4] and Ting & Schonfeld [6] assumed that the transfer demand is known or predictable without a clear description of a prediction method. However, the validity of these assumptions in practical operation of timed transfer coordination control has not been discussed in literature. To the best of the author's knowledge, none of the existing study has developed a real-time prediction model of transfer demand. The fact that this variable is stochastic, discrete and diminutive confounds analyst predictions in real-time.

Individual travel pattern can be used to effectively forecast the transfer demand in real-time because it shows the regular boarding and alighting locations of each passenger. A probability of transferring for each passenger could be estimated by examining travel pattern, which enables anticipating the transfer demand. Passenger travel pattern has been traditionally analysed using stated preference or travel diaries survey data [8, 9]. However, as passengers are making new trips and changing their travel pattern on a daily basis, a new continuous data source is required for transfer demand prediction used in timed transfer coordination.

Recently Smart Card (SC) AFC system has been increasingly popular in public transport, providing a massive quantity of continuous and dynamic data on passenger temporal and spatial movements. It enables continuous analysis of individual travel patterns on a much larger population than the traditional travel survey method. Chu & Chapleau [10] described a disaggregated travel pattern analysis framework for multi-day AFC data. "Anchor points" or repeated travel locations are mined from each SC user and then assigned to known spatial coordinates. Ma *et al.* [11] and Kieu *et al.* [12] adopted the classical DBSCAN algorithm, originally proposed in Ester *et al.* [13], to mine spatial and temporal travel patterns from AFC data. While individual analysis of travel behaviour enables oriented service provision, the classical DBSCAN algorithm has high quadratic computation complexity. Kieu *et al.* [14] proposed a new algorithm based on the same fundamental with classical DBSCAN to solve this quadratic programming problem and rapidly update the individual travel pattern.

In summary, there has been growing interest in the field of timed transfer coordination in operational control. However, little attention has been paid to actual prediction of the transfer demand in real-time, which is the main reason why public transit timed transfer coordination is not as successful and popular as its air transportation counterpart. The hypothesis of this paper is that individual passenger travel pattern can be used to predict transfer demand for timed transfer coordination. Kieu *et al.* [12] shows that the majority of transit trips are made by passengers with regular travel patterns, where those regular customers repeatedly make transit trips of the same origin-destination. The findings of Kieu *et al.* [12], provide a certain level of confidence that the knowledge of individual travel pattern is helpful in predicting the number of transferring passengers in real time. Interested readers should refer to Kieu *et al.* [12] for details.

Methodology

This section describes the method to dynamically predict transfer demand for timed transfer coordination. We focus on the problem of one FV connects with one RV at a single transfer stop.

In timed transfer coordination in operational control, transfer demand prediction forecasts the number of transferring passengers of a FV travelling to the transfer stop. The limited examinations of transfer demand prediction in literature assume that all passengers are homogenous and sharing a similar deterministic transfer probability, so transfer demand only depends on the number of passenger on-board [2, 3, 7]. However, our earlier study shows that different segment of passengers has different travel behaviours [12]. Passengers can have regular spatial or temporal travel patterns, or both of them. Therefore, passengers with a spatial travel pattern of transferring have higher probability of transferring than other passengers.

We develop different analytical, statistical and computational intelligence models to compare and choose the best model in terms of prediction accuracy. While statistical models are descriptive, and represent the statistical properties of data and their dependence on covariates, computational intelligence models such as Artificial Neural Network (ANN) generally would encapsulate the complex relationship between the dependent and independent variables [15]. The following explanatory variables in Table 1 are used to predict the transfer demand.

Table 1 Descriptions of variables used in transfer demand prediction

Name	**Description**
Dependent variables	
N_f	Number of transferring passengers
Independent variables	
1. *HP*	Number of passengers that are likely to transfer
2. *LP*	Number of passengers that are unlikely to transfer
3. *MeanTransfer*	Mean number of transfer at the studied service
4. *MeanLPTransfer*	Mean number of LP that transfer at the studied service
5. *AM*	1 if the time period is AM peak (7-10:00), 0 otherwise
6. *MID*	1 if the time period is midday off-peak (10-14:00), 0 otherwise

This paper assumes that AFC data of both boarding (*touch on*) and alighting (*touch off*) is available in real-time. Figure 1 explains how the variables in Table 1 are obtained from observed data.

The prediction framework starts with a feeding vehicle FV_i approaching the transfer stop, where real-time AFC data provides the list of N_i on-board passengers. Each passenger P_j in FV_i (j=1..N_i) has a probability of transfer at the upcoming transfer stop, which is calculated using the historical travel itinerary of P_j

$$P(P_j^{transfer}) = \frac{\sum transfers_{P_j}}{\sum journeys_{P_j}} \times 100\% \qquad (1)$$

The probability of transfer for each passenger P_j is defined as the ratio between the total number of transfer journeys and the total number of journeys. These two variables are obtained from individual travel itinerary data, which in turn has been established from the historical AFC data. The process of reconstructing travel itinerary from AFC data has been described in various existing studies in literature [12, 14]. If $P(P_j^{transfer})$ is larger than 50%, the passenger is considered as "likely to transfer" because the probability of transferring is larger than otherwise. The sum of "likely to transfer" passengers makes up the HP_i variable, whereas LP_i is the remaining passengers on-board of vehicle FV_i

$$LP_i = N_i - HP_i \qquad (2)$$

Two historical variables mean number of transfer $MeanTransfer_i$ and mean number of LP that transfer $MeanLPTransfer_i$ within the same 30 minutes time window are estimated from the historical itinerary data. Along with two binary variables AM_i and MID_i, these explanatory variables are used in three different types of models: a) Simple analytical model; b) Statistical model; and c) Computational intelligence model to predict the number of transferring passenger in vehicle FV_i.

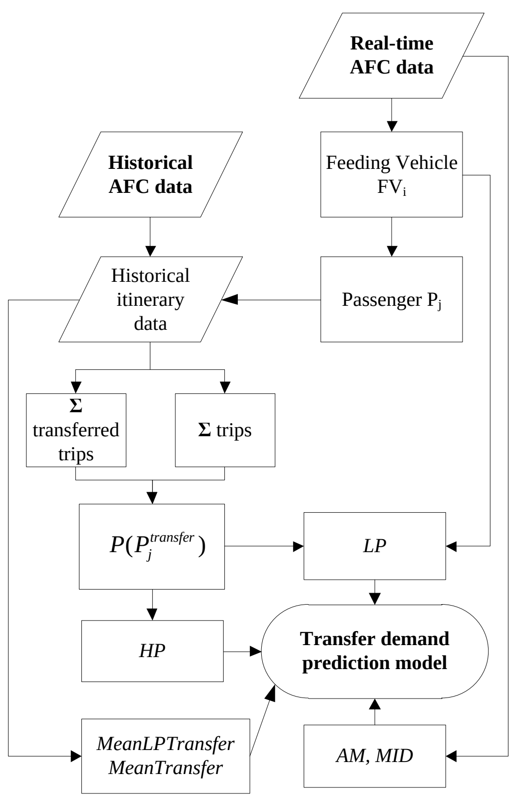

Figure 1 Transfer demand prediction framework

Simple analytical model

Analytical model has a mathematical closed form solution, which is tractable and has high explanatory power. It is therefore the preferable modelling approach whenever it is possible. This sub-section develops a Simple Analytical (SA) model to predict the number of transferring passengers which is based on the idea that if all passengers who are likely to transfer would make the transfer, then we only need to add the average number other passengers to make up the transfer demand. This model provides a simple heuristic approach for transfer demand prediction.

$$N_f = HP + MeanLPTransfer \quad (3)$$

Where

N_f =Number of transferring passengers, to be predicted

HP = Number of passengers that is likely to transfer, i.e. has the individual probability of transfer higher than 50%

MeanLPTransfer = mean number of passenger which is not likely to transfer but transferred during the study period

The model has no intercept because when *HP* and *MeanLPTransfer* are both zero the number of transferring passenger should also be zero.

Statistical model

The number of transferring passengers is a common count data variable, which is a statistical data type in which the observations are non-negative integer values. Count data is common in many disciplines including transportation engineering. Quddus [16] adopted Integer-Valued Auto Regressive (INAR) Poisson time series model to estimate the traffic accidents counts in Great Britain. Frondel and Vance [17] surveyed adult members of German households to examine the determinants of public transport ridership. Zero-inflated models were developed to quantify the effects of fuel price, fare, personal and transit system attributes, as the ridership counts was modelled as count data. Fuel price was identified as having a positive impact on the ridership. This sub-section develop statistical count data model to predict the number of transferring passengers.

Poisson or Negative Binomial distribution is often assumed for modelling the distribution of observed count data. A random variable Y is said to have a Poisson distribution with parameter μ if it takes integer values y= 0,1,2,… with probability:

$$\Pr\{Y = y\} = \frac{e^{-\mu}\mu^{y}}{y!} \quad (4)$$

μ = both mean and variance of this distribution, or in other words, “equi-dispersed” (μ >0)

Here μ refers to the expected transferring passengers, and *y* refers to the observed (real) number of transferring passengers. Poisson Regression models log of μ as a function of independent variable X_j.

$$\ln(\mu) = \sum_{j=1}^{K} \beta_j X_j \quad (5)$$

In this form, the Poisson Regression is relatively similar to the OLS, with the log form of the dependent variable to avoid negative values. The formula can be rewritten as

$$\mu = e^{\sum_{j=1}^{K} \beta_j X_j} \tag{6}$$

Where X_j independent variables (predictors) and regression coefficients β_j are to be estimated using Maximum Likelihood estimation.

However, Poisson regression relies on a strong assumption that the variance of the dependent variable equals its mean. This assumption is often not met in observed data due to its skewness. If the transferring passenger variable is "over-dispersed" or in other words, its variance exceeds the mean, we could also use the Negative Binomial distribution to model the dependent variable. Negative Binomial distribution describes "over-dispersed" count data better but has one more parameter compared to the Poisson Distribution. Its probability function could be written as

$$\Pr\{Y = y\} = \frac{\Gamma(y + 1/\alpha)}{\Gamma(y+1)\Gamma(1/\alpha)} \left(\frac{1}{1+\alpha\mu}\right)^{1/\alpha} \left(\frac{\alpha\mu}{1+\alpha\mu}\right)^{y} \tag{7}$$

Where y= 0,1,2,… in this case it is the number of transferring passengers

μ = mean of this distribution (μ >0)

α = dispersion or heterogeneity parameter, where $\mu + \frac{\mu^2}{\alpha}$ is the variance of this distribution

If the dependent variable has excessive zeros, both the Poisson and Negative Binomial model will under-predict zeros. In this case, a Zero-Inflated Poisson (ZIP) or Zero-Inflated Negative Binomial (ZINB) model will be needed. This type of model assumes two distinct groups of observed dependent variables: Type 0 contains only zero; and Type 1 contains only positive count values. Zero-inflated model is a mix of two processes-one that determines if the individual is eligible for a Type 1 response, and another that determines the count of that response for eligible individuals. The first process uses a logit model to quantify the probability of being eligible for a Type 0 response with probability ω, whereas the second process is a regular Poisson or Negative Binomial Regression model with probability $1-\omega$.

$$ZIP : \Pr\{Y = y\} = \begin{cases} \omega + (1-\omega)e^{-\mu}, y = 0 \\ (1-\omega)\dfrac{\mu^y}{y!}e^{-\mu}, y > 0 \end{cases}$$

$$ZINB : \Pr\{Y = y\} = \begin{cases} \omega + (1-\omega)\left(\dfrac{1}{1+\alpha\mu}\right)^{1/\alpha}, y = 0 \\ (1-\omega)\dfrac{\Gamma(y+1/\alpha)}{\Gamma(y+1)\Gamma(1/\alpha)}\left(\dfrac{1}{1+\alpha\mu}\right)^{1/\alpha}\left(\dfrac{\alpha\mu}{1+\alpha\mu}\right)^{y}, y > 0 \end{cases} \tag{8}$$

We adopt the Vuong test to decide if ZIP and ZINB models are used instead of the classical Poisson and Negative Binomial Regression model or not. The Vuong test [18] is designed to test null hypothesis that

ZIP (or ZINB) is equally close to the observed data as the traditional Poisson (or Negative Binomial) model. The metric of comparison is the Kullback-Leibler divergence, a measure of the distance between two probability distribution. The null hypothesis of the Vuong test is

$$H_0 : D_{KL}(g_t \parallel g_1) = D_{KL}(g_t \parallel g_2) \quad (9)$$

Where $D_{KL}(g_t \parallel g_1)$ measures the Kullback-Leibler divergence between the true model that generate observed data g_t and the model of interest g for nonnegative integers

$$D_{KL}(g_t \parallel g_1) = \sum_{y=0}^{\infty} \ln\left\{\frac{g_t(y)}{g(y)}\right\} g_t(y) \quad (10)$$

Computational intelligence model

In transportation engineering, the most commonly applied computational intelligence paradigm in prediction is backpropagation learning method using Artificial Neutral Network [19]. ANN models the complex nonlinear relationship between the dependent variable and its independent variables, without the need of specifying the exact formulation. ANN is chosen instead of other computational intelligence models, such as Support Vector Machines [20], because of its flexibility, simplicity in implementation and quickness in providing an estimation in real time.

A three-layered, multilayer perceptron ANN model was constructed for predicting the number of transferring passengers. Among the three layers of the ANN model, the first layer is the input layer, where the observed data is presented to the neural network. This data is presented to a 7 neurons input layer, where each neuron holds an independent variable. The last layer is the output layer, producing the estimated response for the input. The output layer has only a single neuron, representing the estimated number of transferring passengers. The intermediate layer is the hidden layer, where non-linear pattern associations between the input and output variables are established.

A global and robust validation procedure is essential to avoid over-fitting, when the error on the training dataset is very small, but the model performs poorly to new unseen data. To avoid over-fitting, the training data is randomly divided to 70% of “developing dataset” and 30% of “cross-validating dataset”. Different ANN models with 1 to 20 neurons in 1 to 3 hidden layers are built from the developing dataset, and a single hidden layer with 9 neurons has been found to be satisfactory using the cross-validation dataset. Figure 2 illustrates the structure of the proposed ANN model.

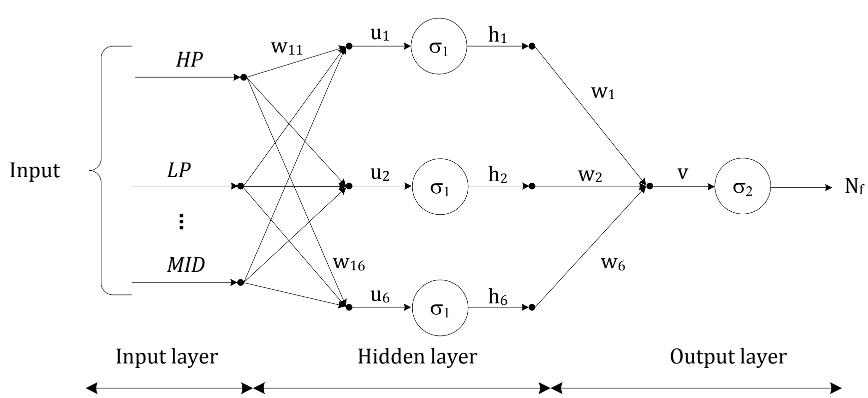

Figure 2 ANN model structure

The prediction error of backpropagation algorithm is calculated by the value of Mean Squares Error (MSE)

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(t_j - m_j)^2 \qquad (11)$$

Where N = number of testing data

t = target output value

m = model output value

Hyperbolic tangent sigmoid transfer function is used in the hidden layer and linear transfer function is used in the output layer. The backpropagation algorithm has the maximum iteration is set as 1000, learning rate as 0.1 and training goal as 0.001.

Numerical examinations

This section examines the prediction accuracy of the aforementioned Simple analytical, Statistical and Computational intelligence models in timed transfer coordination. Four months AFC data from July to October 2013 of two busy bus routes in South East Queensland (SEQ), Australia is used for the comparison. Each record of AFC data includes Smart Card ID, and Stop ID & Timestamp of both touch on (passenger boarding) and touch off (passenger alighting) transactions. Figure 3 illustrates the two routes, where the single transfer stop is the 11th stop of Route 555 and 1st stop of Route 572 (Springwood station).

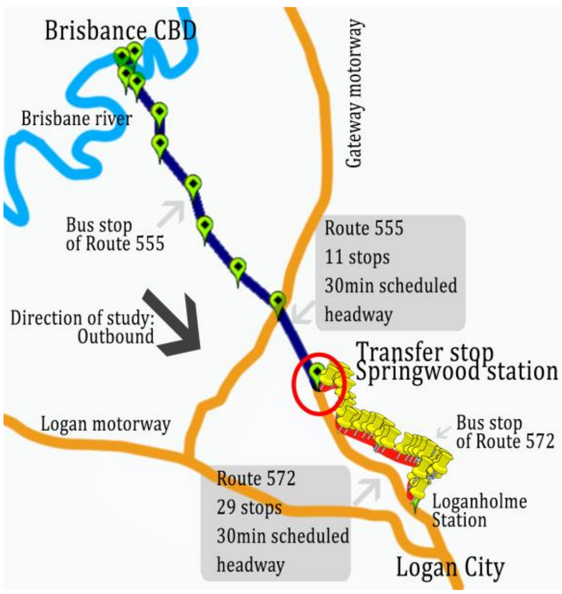

Figure 3 Case study

Route 555 has 15-minute while Route 572 has 30-minute scheduled headway. For this analysis we only consider the services of Route 555 with direct connection with Route 572, i.e. where Route 572 vehicle is scheduled to depart 5 minutes after Route 555 arrival. Both routes therefore can be seen as having 30-minute scheduled headway. Over the 4 months of AFC data there are in total 1031 cases where the receiving vehicle (RV) arrives earlier than the feeding vehicle (FV), so that transfer coordination is meaningful. The first 3 months of data (Jul-Sep 2013), 763 samples, have been used for model development and the rest have been used for model comparison. Table 2 shows the descriptive statistic of the dataset.

Table 2 Descriptive statistic of variables

Name	Sample size	Mean	Std. Dev	Min	Max
Dependent variables					
$\bar{N}_f$	1031	1.34	1.73	0	12
Independent variables					
1. *HP*	1031	1.21	1.57	0	10
2. *LP*	1031	7.49	8.93	0	43
3. *MeanTransfer*	1031	1.41	1.58	0.77	1.69
4. *MeanLPTransfer*	1031	0.19	1.21	0.02	0.43
5. *AM*	1031	0.32	0.47	0	1
6. *MID*	1031	0.25	0.43	0	1

The models are compared using two measures: The Predicting Power (PP) and Root Mean Squared Error (RMSE). PP measures the probability that the prediction model would yield exactly the same number of transferring passengers as the observed data.

$$PP = \frac{\sum_{j=1}^{N} Y_j}{N} \times 100\% \qquad Y_j = \begin{cases} 1 & if\ t_j = m_j \\ 0 & otherwise \end{cases} \tag{12}$$

Where N = number of testing data

t = target output value

m = model output value

While RMSE is a measure of the prediction error.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(t_j - m_j)^2} \tag{13}$$

Table 3 compares the 4 proposed models of transfer demand prediction in terms of RMSE and predicting power (PP).

Table 3 Comparison of 4 prediction models of transfer demand

Model	RMSE	PP (%)
ANN	0.82	55.14
ZIP	0.96	49.37
ZINB	0.97	49.85
SA	1.24	54.8

Overall, ANN shows the lowest prediction error (RMSE) and highest predicting power (PP) compared to all other models. ZIP is slightly better than ZINB in predicting the transfer demand, whereas SA shows the highest RMSE.

Figure 4 compares the 4 models in terms of their prediction errors $RMSE_i$ at each value of transfer demand. The $RMSE_i$ at target output value i (i, number of transferring passengers) is calculated by Eq. (14)

$$RMSE_i = \sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}(i - m_{ij})^2} \quad (14)$$

Where N = number of testing data where the number of transfer demand is i

i = target output value

m_{ij} = model output value

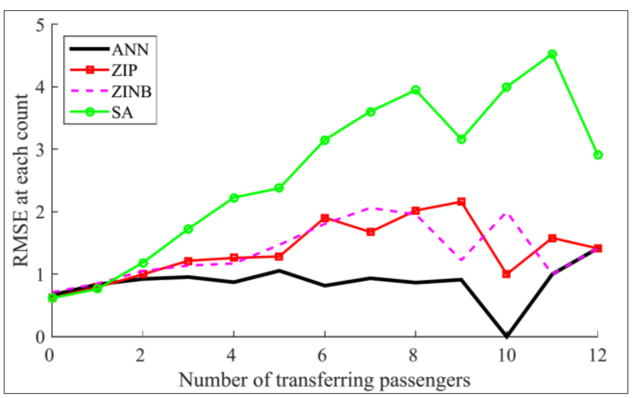

Figure 4 RMSE comparison

Figure 4 shows that ANN has significantly lower RMSE than all other 3 models, especially at high counts (>5) of transferring passengers. The RMSE of ANN is also relatively stable, whereas RMSE of other 3 models increases as the counts increases. Other non-computational intelligence models, especially SA, predict poorly as the transfer demand increases, where the $RMSE_i$ is up to nearly 5. Similarly, Figure 5 compares the predicting power of the models for different number of transferring passengers.

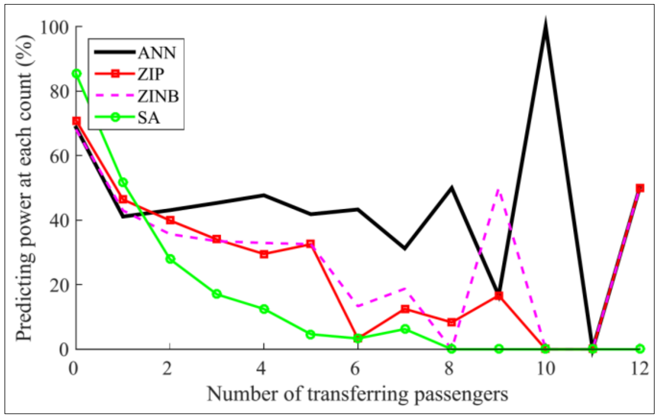

Figure 5 PP comparison

Figure 5 illustrates that ANN has higher predicting power than the other three models, especially when the transfer demand is larger than 2. While all models show good predicting powers of 70-80% at zero count, only ANN maintains the predicting power of around 40% at counts of 1-8. Because counts 8-12 contribute to very little sample size, all models show fluctuations in predicting power. The comparisons in RMSE and PP demonstrate that ANN is superior to ZIP, ZINB and SA in predicting the number of transferring passengers. Figure 6 provides snapshots of prediction errors and observed transfer demand for two random days from 7 AM to 10 PM. The stacked columns show the prediction error, calculated as predicted minus observed number of transferring passenger on an FV at a scheduled transfer time. The dashed line shows the observed transfer demand.

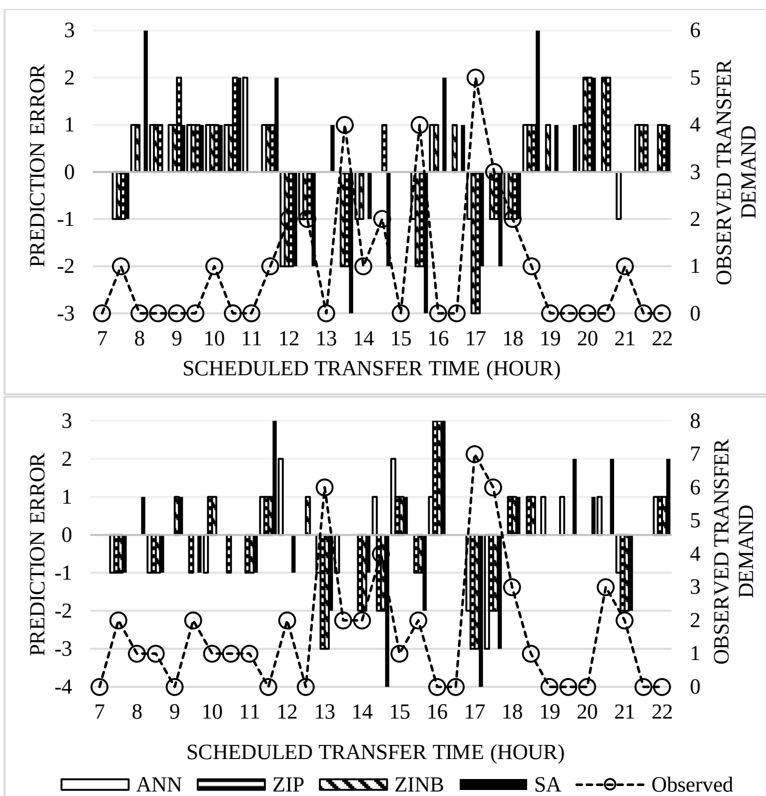

Figure 6 Prediction errors versus observed transfer demand: Snapshots from two random day

The snapshots in Figure 6 show two important points discussed earlier in Figure 4 and Figure 5: (1) SA performs worst among the models, and (2) the models generally performs worse at larger counts of the transfer demand.

Timed transfer coordination strategy framework

This section proposes a simple coordination framework to evaluate the performance of four proposed transfer demand prediction models in real-time timed transfer coordination. Both holding and no holding decision in timed transfer coordination will induce some Extra Waiting Time (EWT) into transferring or non-transferring passengers. In holding decision, transferring passengers will have zero transferring time, but non-transferring passenger of the RV may have EWT, depends on whether the arrival time of the FV is before or after RV's scheduled departure time. In no holding decision, transferring passengers will have to wait for an extra full headway for the next RV service, while non-transferring passengers will experience no EWT. There are generally two cases where the RV arrived earlier or sooner than its schedule.

1) Case 1: RV has just arrived at current time A_r, and it has arrived sooner than its schedule S_r (in minutes from 0:00)

The EWT_r (min) for non-transferring passengers of the RV, once transfer coordination decision has been issued is expressed as:

$$EWT_r = \begin{cases} \left(A_f - S_r + LT_e / 60\right) \times N_r & if \quad A_f > S_r \\ 0 & \quad\;\; A_f \le S_r \end{cases} \tag{15}$$

Where EWT_r = total EWT of non-transferring passengers of the RV at transfer coordination strategy (min)

r = index of the RV being controlled at the transfer stop

f = index of the FV approaching the transfer stop

A_f = arrival time of the FV to the transfer stop (min from 0:00)

S_r = schedule departure time of the RV from the transfer stop (min from 0:00)

N_r = number of non-transferring passengers of the RV

LT_e = extra loading time induced by extra passengers (transferring passengers) boarding the RV (seconds). LT_e is the compilation of the lost time of FV stopping, passenger alighting time from FV, passenger walking time to RV, and passenger boarding time to RV.

Holding time is the amount of time that RV is held beyond its scheduled departure time S_r to wait for FV's arrival.

$$Holdingtime = \begin{cases} A_f - S_r + LT_e/60 \;\; if \;\; A_f > S_r \\ 0 \;\; if \;\; A_f \le S_r \end{cases} \quad (16)$$

In reality, the holding time cannot exceed a predefined Slack Time (*ST*) because holding RV for too long is undesirable for on-board passengers and deteriorates downstream schedules [2].

$$Holdingtime \le ST \quad (17)$$

Conversely, if no transfer coordination has been issued, the EWT for transferring passenger to wait for the next service is calculated as

$$EWT_f = \begin{cases} \left(S_r + H - A_f - LT_e/60\right) \times N_f \;\; if \;\; A_f > S_r \\ 0 \qquad A_f \le S_r \end{cases} \quad (18)$$

Where EWT_f = total EWT of transferring passengers at no transfer coordination strategy (min)

H = schedule headway of the RV (min)

N_f = number of transferring passengers from FV to RV

Figure 7 illustrates Case 1 of the timed transfer in operational control problem

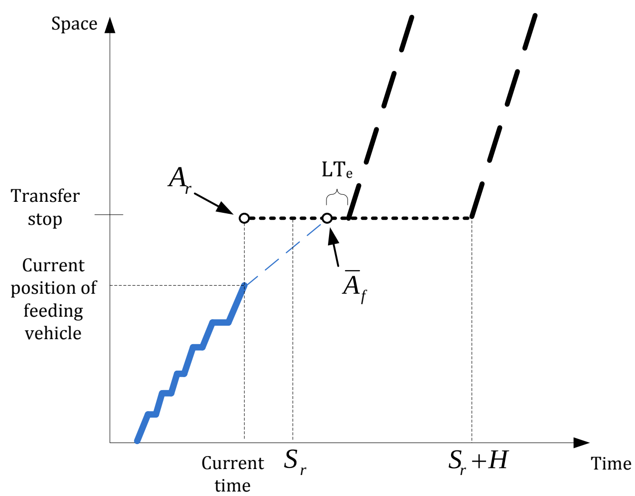

Figure 7 Timed transfer in operational control: Case 1 ($A_r < S_r$)

2) Case 2: RV arrived later than its schedule ($S_r \le A_r < A_f$)

The EWT_r (min) for non-transferring passengers of the RV, once transfer coordination decision has been issued

$$EWT_r = \left(A_f - A_r + LT_e/60\right) \times N_r \quad (19)$$

Where A_r = actual arrival time of the RV to the transfer stop (min from 0:00)

The holding time needed in this case is

$$Holdingtime = A_f - A_r + LT_e / 60 \tag{20}$$

Similar to the previous case, this control is subject to the limit in the amount of planned ST

$$Holdingtime \leq ST \tag{21}$$

Conversely, if no transfer coordination has been issued, the extra cost for transferring passenger to wait for the next service could be calculated as

$$EWT_f = \left(S_r + H - A_f - LT_e / 60\right) \times N_f \tag{22}$$

Figure 8 illustrates Case 2 of the timed transfer in operational control problem

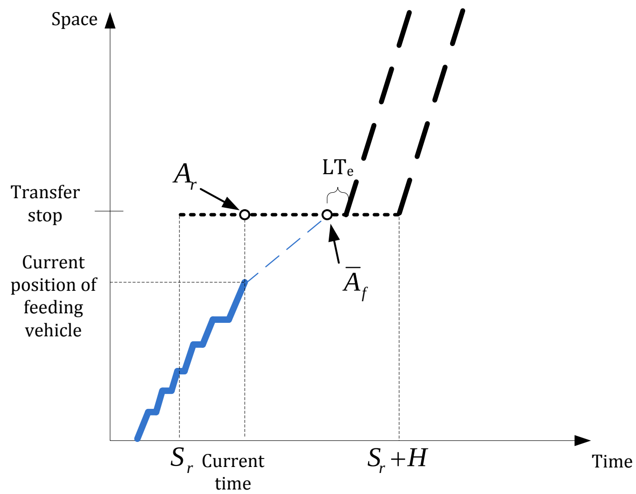

Figure 8 Timed transfer in operational control: Case 2 ($S_r \leq A_r < A_f$)

The timed transfer coordination control model solves a simple binary optimisation problem to choose the holding decision which cause least EWT to transferring and non-transferring passengers. RV is held if $\overline{EWT_r} \leq \overline{EWT_f}$ and leaves as scheduled otherwise. Where $\overline{EWT_r}, \overline{EWT_f}$ are the predicted EWTs of non-transferring and transferring passengers, calculated using Equation (15) to (22). However, because the transfer demand (N_r), non-transfer demand (N_f), and vehicle arrival time (A_f) are unknown in real-time, $\overline{EWT_r}$ and $\overline{EWT_f}$ are predicted using forecasted variables $\overline{N}_f$, $\overline{N}_r$, and $\overline{\mathrm{A}}_f$. The controlled departure time CD_r after timed transfer coordination could be calculated in Eq. (23).

$$CD_r = \begin{cases} Max(S_r, \mathrm{A}_r, \overline{\mathrm{A}}_f : \text{if } \overline{\mathrm{A}}_f < S_r + ST) & if \quad \overline{EWT_r} \leq \overline{EWT_f} \\ Max(\mathrm{A}_r, S_r) & if \quad \overline{EWT_r} > \overline{EWT_f} \end{cases} \tag{23}$$

Sensitivity analysis of transfer demand prediction in timed transfer coordination

The proposed timed transfer coordination framework is empirically experimented using the same case study of Route 555 and Route 572 in SEQ, Australia as illustrated in Figure 3, using AVL and AFC data of October 2013.

The predictions of $\overline{EWT_r}$ and $\overline{EWT_f}$ require forecasted values of $\overline{N}_r$, $\overline{N}_f$ and $\overline{A}_f$. Because predictions of non-transferring passenger demand ($\overline{N}_r$) and vehicle arrival time ($\overline{A}_f$) has been extensively studied in literature [20-22], this sub-section only examines the applicability of transfer demand prediction ($\overline{N}_f$) in timed transfer coordination. Given exact predictions of $\overline{N}_r$ and $\overline{A}_f$, Figure 9 compares the extra waiting time per passenger when the timed transfer coordination framework is implemented using different transfer demand predictor at different values of slack time (in minutes).

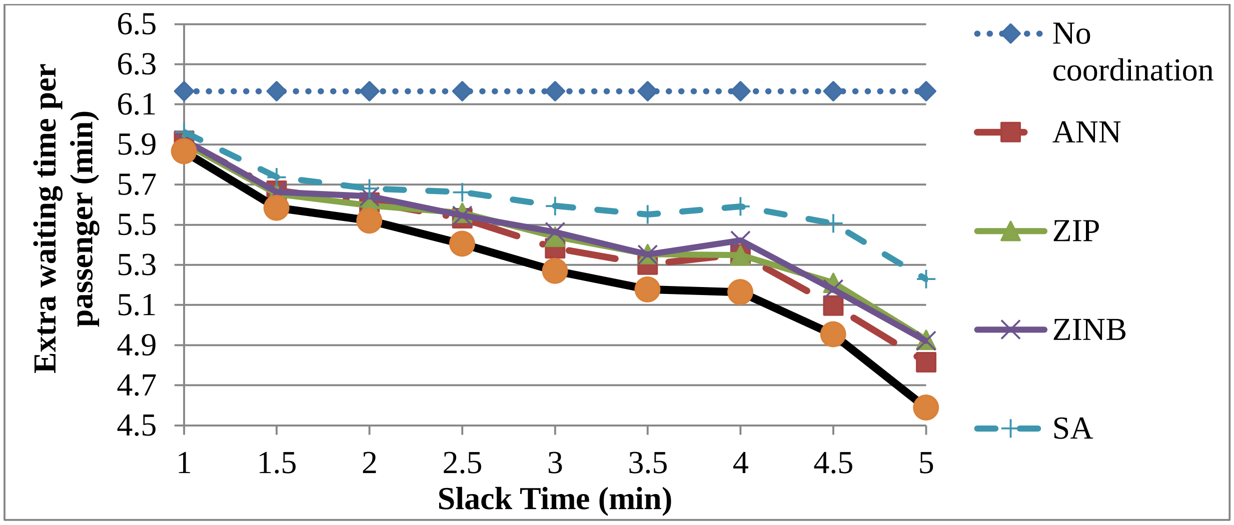

Figure 9 Comparison of timed transfer coordination using different transfer demand predictor

Figure 9 shows timed transfer coordination in general reduces the EWT per passenger, regardless of transferring or non-transferring, compared to the no coordination case. ANN shows the largest reduction in EWT compared to no coordination, while SA has the worst performance. If the transfer demand is known in real time, EWT per passenger can be further reduced by an additional 4.8% as compared to that of ANN. This indicates, further improvements in transfer demand prediction model should provide more benefits in reducing EWT per passenger with the proposed timed transfer coordination strategy.

According to the Table 3, these models have relatively low predicting power, denotes that the models sometimes fail to predict the exact number of transferring passengers. However, the reductions in EWT are promising because of the relatively low RMSE, where the proposed predictors were able to forecast with approximately 1 passenger deviation from the observed value. Table 4 provides a lookup table to select a transfer demand predictor to be used in proposed timed transfer coordination strategy according to its accuracy and computation time cost for real time applications.

Table 4 Descriptive statistic of proposed transfer demand prediction models

Model	Variables	Training	Computation	RMSE	PP (%)	Saved

	required	time (min)	time* (min)			EWT** (%)
ANN	6	560	0.04	0.82	55.14	21.9
ZIP	6	205	0.01	0.96	49.37	20
ZINB	6	221	0.01	0.97	49.85	20.3
SA	2	0	<0.01	1.24	54.8	15.2

**Computation time is the time required for a trained model to provide prediction given all the inputs, both training and computation tasks were performed using Matlab R2015a using an Intel Core i5-2520M computer with 8GB Ram.*

***Saved EWT compared to no coordination, when ST equals 5 minutes*

ANN provides the most accurate prediction, but also requires more time than any other model for training and predicting. Conversely, SA shows the lowest prediction accuracy and also worst performance in timed transfer coordination, but requires the least time & variables with a closed-form solution. Figure 4 and Figure 5 suggest that while the proposed models provide similar performance at low target values (e.g. *i* equals 0, 1 or 2), ANN provides significantly better prediction when the number of transferring passengers is larger. More transferring passengers generally means that transfer coordination is necessary. ANN therefore should be chosen as the predictor if there is more transfer demand, whereas SA should be chosen when a simple closed form solution is favourable in a system with less transfer demand.

Sensitivity analysis of HP

HP is an important variable in transfer demand prediction, denoting the number of passengers who have high probability of transferring, or are “likely to transfer”. The definition of HP decides the value of parameters HP and LP. If the threshold for “likely to transfer” is low, the value of HP is large, but for each passenger the confidence that he/she would actually transfer is low, and vice versa. Figure 10 shows SA and ANN’s prediction performance at different value of “likely to transfer” threshold.

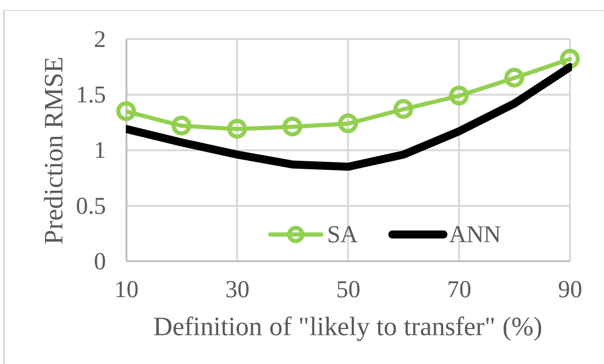

Figure 10 Sensitivity analysis of the definition of HP

Both SA and ANN show higher prediction error when the definition of “likely to transfer” is too low or too large. Generally SA always yields larger prediction error than ANN at all values.

Conclusion

This paper introduces a new transfer demand prediction method for real-time timed transfer coordination. The transfer demand is predicted using individual passenger travel pattern by examining each passenger historical travel itineraries. Four predictors of transfer demand have been developed: ANN, ZIP, ZINB and SA. Here, ANN outperforms the other models, while SA takes the least time to train and compute. When experimented using observed AVL and AFC data from SEQ, Australia, timed transfer coordination using these models reduces EWT per passenger up to 21.9% as compared to no coordination.

This paper is one of the first to predict the number of transferring passenger in real time and to show that timed transfer coordination is effective using forecasted transfer demand. It provides the missing link to a better transfer service in public transit. Transit agencies can choose between artificial intelligence models of higher accuracy but without a closed-form solution when the transfer demand is large, or statistical and analytical models of lower accuracy but with an interpretable formulation when the transfer demand is low.

This paper only thrives to show the possibility of predicting the transfer demand in real time using a simple transfer coordination case study of a single receiving and feeding transit line. Future examinations include the impacts of transfer demand prediction on a transit network of multiple connected lines.

Acknowledgment

Data used in this study was provided by Translink, the transit authority of South East Queensland, Australia. The conclusions in this paper reflect the understandings of the authors, who are responsible for the accuracy of the data.

Reference

[1] F. Creutzig and D. He, "Climate change mitigation and co-benefits of feasible transport demand policies in Beijing," *Transportation Research Part D: Transport and Environment*, vol. 14, pp. 120-131, 3// 2009.

[2] M. Dessouky, R. Hall, A. Nowroozi, and K. Mourikas, "Bus dispatching at timed transfer transit stations using bus tracking technology," *Transportation Research Part C: Emerging Technologies*, vol. 7, pp. 187-208, 8// 1999.

[3] M. Dessouky, R. Hall, L. Zhang, and A. Singh, "Real-time control of buses for schedule coordination at a terminal," *Transportation Research Part A: Policy and Practice*, vol. 37, pp. 145-164, 2// 2003.

[4] E.-H. Chung and A. Shalaby, "Development of control strategy for intermodal connection protection of timed-transfer transit routes," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2006, pp. 3-10, 2007.

[5] M. Chowdhury and S. Chien, "Dynamic Vehicle Dispatching at the Intermodal Transfer Station," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1753, pp. 61-68, 01/01/ 2001.

[6] C. J. Ting and P. Schonfeld, "Dispatching control at transfer stations in multi-hub transit networks," *Journal of Advanced Transportation*, vol. 41, pp. 217-243, 2007.

[7] B. Yu, S. Wu, B. Yao, Z. Yang, and J. Sun, "Dynamic vehicle dispatching at a transfer station in public transportation system," *Journal of Transportation Engineering*, vol. 138, pp. 191-201, 2011.

[8] T. Adler and M. Ben-Akiva, "A theoretical and empirical model of trip chaining behavior," *Transportation Research Part B: Methodological*, vol. 13, pp. 243-257, 9// 1979.

[9] K. G. Goulias, "Longitudinal analysis of activity and travel pattern dynamics using generalized mixed Markov latent class models," *Transportation Research Part B: Methodological,* vol. 33, pp. 535-558, 11// 1999.
[10] K. K. A. Chu and R. Chapleau, "Augmenting Transit Trip Characterization and Travel Behavior Comprehension: Multiday Location Stamped Smart Card Transactions," *Transportation Research Record: Journal of the Transportation Research Board,* vol. 2183, pp. 29-40, 2010.
[11] X. Ma, Y.-J. Wu, Y. Wang, F. Chen, and J. Liu, "Mining smart card data for transit riders' travel patterns," *Transportation Research Part C: Emerging Technologies,* vol. 36, pp. 1-12, 2013.
[12] L. M. Kieu, A. Bhaskar, and E. Chung, "Passenger Segmentation Using Smart Card Data," *IEEE Transactions on Intelligent Transport System,* vol. 16, p. 1537, 2015.
[13] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu, "A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise," in *Second international conference on knowledge discovery and data mining,* 1996, p. 226.
[14] L. M. Kieu, A. Bhaskar, and E. Chung, "A modified Density-Based Scanning Algorithm with Noise for spatial travel pattern analysis from Smart Card AFC data," *Transportation Research Part C: Emerging Technologies,* vol. 58, pp. 193-207, 2015.
[15] T.-H. Tsai, C.-K. Lee, and C.-H. Wei, "Neural network based temporal feature models for short-term railway passenger demand forecasting," *Expert Systems with Applications,* vol. 36, pp. 3728-3736, 2009.
[16] M. A. Quddus, "Time series count data models: An empirical application to traffic accidents," *Accident Analysis & Prevention,* vol. 40, pp. 1732-1741, 2008.
[17] M. Frondel and C. Vance, "Rarely enjoyed? A count data analysis of ridership in Germany's public transport," *Transport Policy,* vol. 18, pp. 425-433, 3// 2011.
[18] Q. H. Vuong, "Likelihood ratio tests for model selection and non-nested hypotheses," *Econometrica: Journal of the Econometric Society,* pp. 307-333, 1989.
[19] U. Gazder and N. T. Ratrout, "A new logit-artificial neural network ensemble for mode choice modeling: a case study for border transport," *Journal of Advanced Transportation,* pp. n/a-n/a, 2015.
[20] B. Yu, Z. Z. Yang, and K. Chen, "Hybrid model for prediction of bus arrival times at next station," *Journal of Advanced Transportation,* vol. 44, pp. 193-204, Jul 2010.
[21] Z. Ma, J. Xing, M. Mesbah, and L. Ferreira, "Predicting short-term bus passenger demand using a pattern hybrid approach," *Transportation Research Part C: Emerging Technologies,* vol. 39, pp. 148-163, 2014.
[22] M. Chen, J. Yaw, S. I. Chien, and X. Liu, "Using automatic passenger counter data in bus arrival time prediction," *Journal of Advanced Transportation,* vol. 41, pp. 267-283, Fal 2007.