



Effect of walking and waiting times on travel time

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Highlights

- Developing a model approach with bus travel time estimation
- Investigating walking and dwell time
- Formulating and solving a between walking time and travel time
- Carrying out analysis and discussing the impact of walking time on bus travel time

Abstract

Real-time travel time estimation has nowadays been becoming increasingly important for advanced passenger information systems, traffic management systems, route guidance systems that are part of Intelligent Transportation Systems (ITS). The widespread use of ITSs around the world has increased access to large amounts of historical and real-time status data. The estimation of bus travel time attracts the attention of many researchers in the literature. The aim of this study is to develop a model for estimating public transport travel. It is seen that passenger waiting times are generally considered when bus travel time models are examined in the literature. This study, unlike other studies, the walking time of the passenger to the bus stops are taken into account. The proposed model is determined with five public transport routes data in the city of Isparta, Turkey. As a result, walking time appears to be effect for travel time. A simple regression model for travel time modeling is presented in the study. Results showed that It is better to include walking time to estimate travel times at least using simple regression models.

Keywords: transportation, travel time estimation, walking and dwell time

Information

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1. Introduction

Bus travel time is the most important parameter for improving public transport. The sum of the travel time of the passenger to the bus stop, the waiting time at the bus stop and the time until the end of the trip is the travel time of the passenger. The main purpose of this study is to create a mathematical model of travel time by determining the effective parameters required to improve the travel time of public transportation.

In general, public transportation system aims to provide comfortable and reliable service. In order to plan bus departure times effectively, travel times must be estimated accurately. In this way, operators may manage public transportation systems more effectively. Therefore, travel time estimation is important for real-time transportation planning [1]. In general, time of arrival of the bus to the stops are stochastic due to the variability of walking and waiting time. Therefore, it is difficult to determine the arrival time estimation models.

Travel time estimation has been studied extensively in the last decades. In the literature, the artificial neural network or Support Vector Machine (SVM) regression method [2-5]; time series [6] and the Kalman filtering technique [3,7,8] have been used. Passengers can plan their transit departure times efficiently and successfully transfer at transit stations with the arrival time information. It will increase the quality of service by reducing the waiting times of passengers as a result, it will attract more passengers [9,10].

For transit planners and operators, the use of real survey data is important to evaluate the performance of the bus route and improve the service level. Automatic Vehicle Location (AVL) system is used to collect data from buses. Studies using AVL data for public transportation are increasing in the literature. Two integrated models for controlling AVL systems are produced [11]. Studies has been focused on measuring the benefits of using AVL data to increase reliability [12,13]. For the metropolitan area of Portland, Oregon, the transit provider Tri-Met

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compared before and after implementation of the Bus Dispatching System (BDS) [12]. BDS used archived AVL and Automatic Passenger Counter (APC) data about the service planned for the Tri-Met to evaluate the actual bus run time change [14]. AVL data was investigated the mass transit operation control strategy for stopping-skipping control, keeping control, and disembarking by barter [15]. A simulation model based on archived AVL data has been developed to estimate the effects on service reliability when real-time AVL information is used [16].

Public transportation system can effectively schedule their departure times. Accurate prediction of bus travel time is difficult to accomplish, and many researchers have studied this problem. Bus travel time is affected by a lot of factors such as passenger walking time and passenger waiting time, bus dwell time at the bus stop and at last bus running time at the link. This study investigates the effect of walking and waiting times on bus travel time in urban areas by using the mathematical models.

This study is organized as follows: First, a brief introduction about bus travel time estimation is provided; then the results and analysis, including the performance estimation of the methodology are given. Finally, the results obtained are presented in last section.

2. Literature Review

Bus travel time prediction models include Kalman filter, ANN models, analytical approaches, and regression models. The parameters that affect the travel time: demand and dwell time, temporal variables and scheduling, bus progress data, historical travel time and speed [17-21] as can be seen in Table 1.

Three general approaches have been developed for bus travel times. The first one is the Kalman Filter Model and the second one is the analytical model one the third one is the regression model.

2.1. Kalman filter model

The Kalman filter is an archived linear sequential prediction algorithm used to predict a future event based on the experience of the latest real-time observation data. Kalman Filter, which is used first, estimates the travel time using archived data provided from the automatic location information system. It estimates the travel speed of the bus from the speeds archived with the second Kalman Filter. Travel time is calculated using the estimated bus travel speed and distance. Unlike ANN and regression models that can be adjusted based on archived data, Kalman filter can respond to dynamic conditions in the model process. Simultaneous data collected from passenger information systems and archived data in travel time estimation are studied with simulation data to increase the performance of the ANN model [2]. Arrival

time at each bus stop, link speed, link traffic flow, link density, etc. is estimated by ANN as a function of simulation data. The Kalman filter changes the arrival time of each bus based on the error of time the bus arrives from one stop to the next stop. Average travel time of vehicles in each time interval; In the following time periods, it is used as the correct value for travel time estimation and is given in Equation 1.

$$x(t)=\phi(t-1)x(t-1)+w(t-1) \quad (1)$$

where $x(t)$ is the estimate of travel time at time, $\phi(t)$ is the transition parameters at time, $w(t)$ is the zero mean and normal distribution noise term in variance.

$$z(t)=x(t)+v(t) \quad (2)$$

In Equation 2, $z(t)$ represents the travel time observed at time t . It is derived from the travel time between two RFID readers placed in the work area. $v(t)$ expresses measurement errors at time t [22].

2.2. Analytical models

In various studies, passenger information system data are used to estimate bus travel time with analytical approaches. However, these approaches have been developed depending on the current situation or specific conditions of each study. A mathematical model has been developed using GPS data to provide real-time travel time information to the urban bus service [23]. Bus location data, time information, the difference between planning and actual access time, and dwell times at the designated stops are used as main model variables. The algorithm is originally developed in rural areas where there is no or minimal traffic congestion.

2.3. Regression model

Regression model provides a simple and highly interpretable process for bus travel time estimation as a function of various parameters such as distance, location of bus stops, etc. It is observed that the current properties of the data are not linear [24,25]. However, unlike regression models, Kalman filter and analytical models are difficult to apply and interpret, and these methods suffer from a slow learning process [4,26,27].

3. Case Study

Isparta is located in the south of Turkey. It is surrounded by the provinces of Afyon, Antalya, Burdur and Konya. Isparta has a population of about 450.000 in 2019. The public transport service is operated by the Private Public Bus (PBS), which has a fleet of approximately 94 buses. All buses are equipped with GPS devices. There are 47 bus routes in the City. The public transport demand is about 25.200 pass/day.



Table 1. Variables used for travel time in the literature

	Shalaby and Farhan [20]	Patnaik et al. [21]	Sun et al. [22]	Chen et al. [23]	Mishalani et al. [24]
Demand/dwell time	√	√		√	
Temporal/variables scheduling		√		√	
Bus progress data			√	√	
Historical travel time/speed	√		√		√

The selected five lines are connected to the important arteries of the city such as Mimar Sinan Street, Hastane Street, Halil Hamit Paşa Street, Süleyman Demirel Street within the study area and the route of each line is shown in the Figure 1.

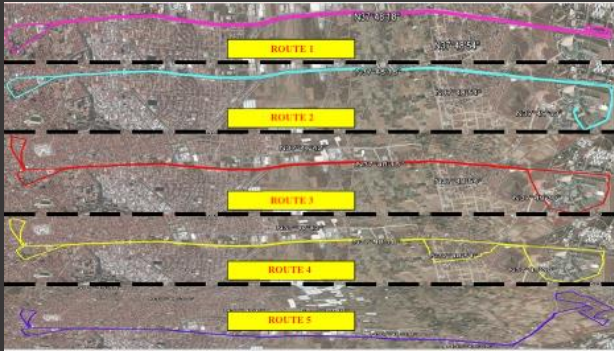


Figure 1. Five routes

Route lengths are approximately between 16 km and 22 km. There are at least 40 and at most 69 stations on the routes. Route 5 has the lowest number of passengers per day. Route 1 has the highest number of passengers per day when the five routes are examined in Table 2.

Table 2. Five routes and their features.

Routes Number	Number of Bus stops	Signalized Intersection Number	Line Length (km)	Daily Passenger Number (pass/day)
Route 1	40	17	16.585	8453
Route 2	44	17	19.036	4487
Route 3	50	20	19.633	3736
Route 4	43	16	18.481	4989
Route 5	69	18	22.383	3526

These data are taken from Isparta Municipality's private public buses. It has been seen that the route with the highest number of stops is the 5th route and the route with the least number of stops is the 4th route.

4. Bus Travel Time Prediction Model

The average travel time of the buses are analyzed for five lines for which line analysis are conducted. First of all, the average speed values of the bus are calculated. In this calculation, the ratio of the distance between the stops

(m) to the time between the stops (s) is found as the average speed value (m/s). Using historical data, the estimated travel time between two successive time points and the other estimated passenger arrival speed are calculated to calculate the waiting time at a time point. This study, a model is form to predict the bus travel time and route analysis.

Bus Travel Time estimation model, which is widely used in the literature, can be seen in Equation 3.

$$\sum_{i=1}^{i=E} T_{iE} = T_{i_{WW}} + \sum_{i=1}^{i=E} T_{i_{BT}} + \sum_{i=1}^{i=E} T_{i_{BD}} \quad (3)$$

Where, $T_{i_{WW}}$ passenger waiting time at the bus stop, $T_{i_{BT}}$ travel time of bus between stops i and E , $T_{i_{BD}}$ delay time of bus stop i from E stop.

In this study, the route analysis results of the five lines with the highest passenger density in Isparta are examined and a travel time model is developed. With this model, travel time is equal to the sum of average of the passenger walking and waiting time, the average travel time of the bus, the waiting time of the bus at the station and the delay time of the bus. The proposed model is given in Equation 4.

$$T_{ij} = \sum_{j=1}^j \frac{T_V + T_B}{2} + T_{OSS} + T_{ODBS} + T_{OBB} \quad (4)$$

where; T_{ij} bus travel time (i : start point, j : end stop), T_V walking time of the passenger, T_B waiting time at bus stop, T_{OSS} average travel time of the bus T_{ODBS} dwell time of the bus at the station, T_{OBB} The delay time of the bus at the starting stop (when $i = 1$) and the passenger unloading time at the last stop ($j =$ the last stop number). It takes $T_{OBB} = 0$ for other i values.

A question-answer questionnaire is conducted for public transport passengers at the bus stops. Equation 4 is used to determine the sample size [28].

$$n = \frac{N \times \sigma^2 \times Z_{\alpha}}{(N-1) \times d^2} \quad (5)$$

where; n sample size, N universe unit number, $\alpha = 0.05, 0.01, 0.001$ value, σ standard deviation, d sampling error.

The sample sizes according to the number of daily passengers are calculated with this equation. As a result of the calculation, the sample size was found to be approximately 137. Survey was carried out for routes 1,2,3,4,5 and found as 390, 186, 766, 506, 158, respectively. Questions about walking and waiting time in the questionnaire: “How long (minutes) does it take to walk to the bus stop: minutes” and “How long (minutes) does it take to wait at the stop: minutes”.

The time during which the passenger walks the distance between the departure point and the vehicle stop point is the walking time. The waiting period is the time elapsed from the moment the passenger arrives at the bus stop until the time he/she gets on the bus. In the question-and-answer questionnaires at the bus stop, walking time and waiting time information are obtained. The arithmetic average of the walking and waiting times of the stops where the passengers boarded are considered.

The walking and waiting times for the stops where the passengers board each of the five routes are given in Figure 2. In Figure 2, the horizontal axis indicates the bus

stop numbers and vertical axis indicates corresponding walking times and the right vertical axis indicates waiting times. While the blue colored dots and the averaged line indicate the walking times corresponding to the stops, the orange-colored dots and the averaged routes indicate the waiting times in Figure 2.

In this study, the travel time model is presented by considering the passenger walking and waiting time at the bus stop as the main parameters. Table 3 shows the arithmetic mean and standard deviations of walking and waiting times.

The arithmetic means and standard deviation values of walking and waiting times are given in Table 3. It shows that route 3 with the highest arithmetic mean of walking time. The standard deviation value is calculated is high due to the difference between values in route 5. The arithmetic mean values of walking time are between about 5 and 8 minutes. Waiting time arithmetic average values are between about 4 and 9 minutes. The standard deviation is high due to the difference between values in route 4.

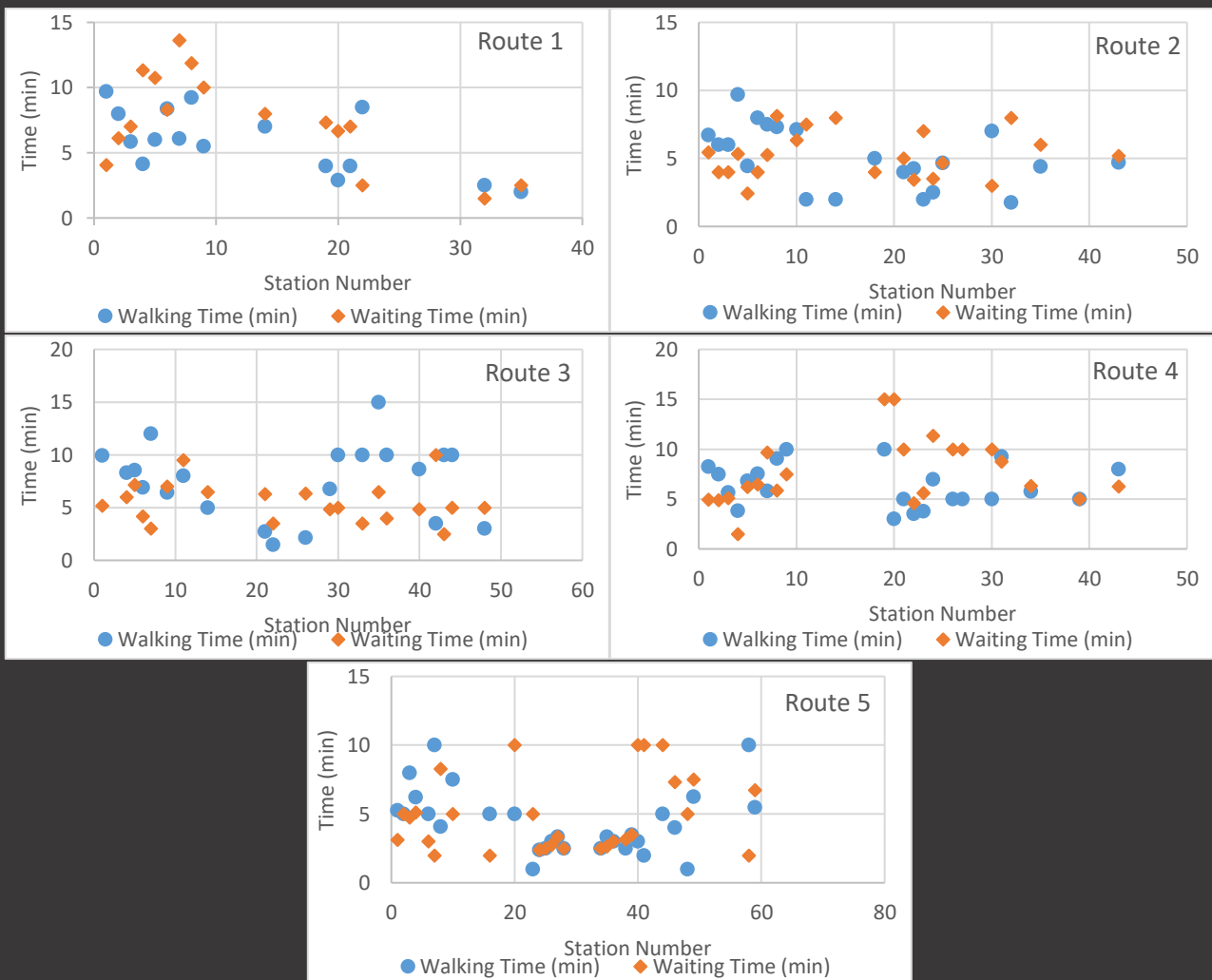


Figure 2. Walking and waiting time to bus stop of five route

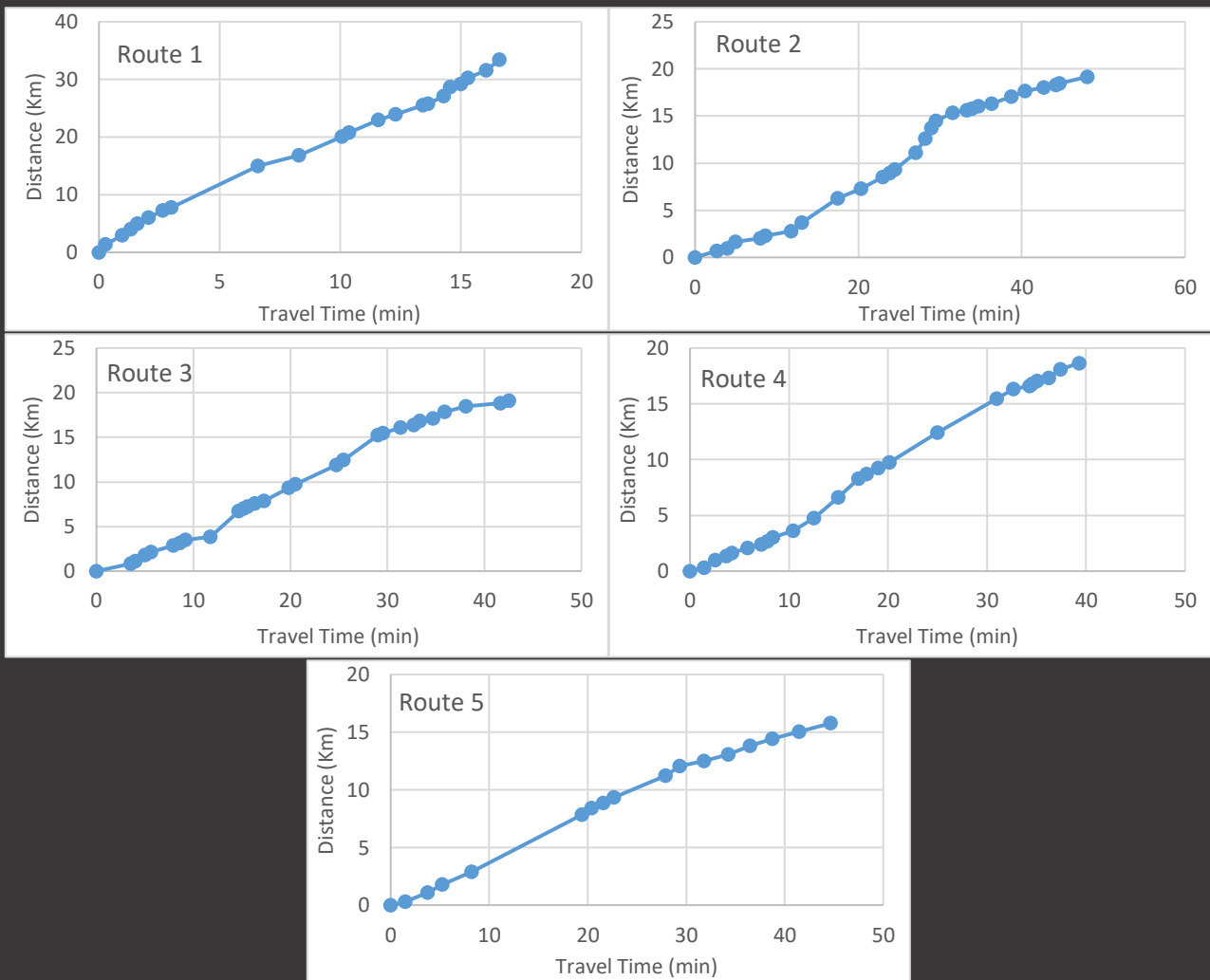


Figure 3. Travel time and distance relationship for routes

Table 3. Arithmetic mean and standard deviation value of walking and waiting time

Routes Number	Walking Time (min)		Waiting Time (min)	
	Arithmetic Mean (μ)	Standard Deviation (σ)	Arithmetic Mean (μ)	Standard Deviation (σ)
Route 1	5.86	2.37	8.12	4.71
Route 2	5.11	2.2	5.91	2.41
Route 3	7.54	3.44	5.52	1.91
Route 4	6.35	2.07	7.72	3.29
Route 5	5.25	5.20	4.16	2.33

As a criterion for the selection of the bus stop, the passenger walking time to the bus stop and the waiting time at the bus stop are effective parameters. Passenger walking and waiting time obtained are important in determining passenger travel time and predicting bus arrival time.

5. Data Collection and Processing

In this study, speed is estimated from the data collected based on connection length and travel time. The data was collected by traveling on a bus in 2015. The travel time of the two bus stops consists of the waiting time at the bus stop during the peak hour period and the walking time of

the passenger to the stops. The waiting period is reached at weekday stops (7:30 - 8:30 and 16:30 - 17:30 pm) and during off-peak periods (12:00 - 13:00 pm). The distance and travel time figures of the four routes are obtained in Figure 3 According to the collected data.

The travel time is equal to the arithmetic average of the walking and waiting time from the moment the passenger starts his/her journey to the stop, the average travel time of the bus and the delay time of the bus by interpreting the collected data. One of the most important parameters affecting travel time is the stops. After reaching a certain speed, the bus should slow down and accelerate to stop at the stop for the passenger to reach the same speed after getting on and off. The time a bus stays at the station starts with the opening of the door. It ends with the door closing after the passengers get off or get on. It is assumed that 6 seconds are added for closing and opening the doors since the time between opening and closing the door. Regression analysis expressing the mathematical model of the relationship between travel time and distance is examined for the routes. Regression analysis results for 5 routes for the travel time model are given in Table 4.

Table 4. Regression analysis of routes.

Routes Number	Multiple R	R Square	Standard Error
Route 1	0,99	0,99	0,39
Route 2	0,98	0,97	1,1
Route 3	0,99	0,98	0,72
Route 4	0,99	0,99	0,46
Route 5	0,99	0,98	0,58

It can be seen in Table 4 that the multiple R is close to 1 in the regression model. This situation shows the suitability of the model. The R squared value indicates the total variable of the explanatory variable in the dependent variable. Route 1 and Route 4 explain 99% of the total change. The results show that the regression model is found to be significant. The reason for the quite high standard error value in route 2 is the difference between collected data values.

6. Conclusion

This study investigates the effect of walking and waiting times on travel time for bus routes based on AVL data. Passenger demand for the routes, the walking times of the passengers and the waiting times of the passengers at the bus stop, and the travel time between the stops are considered for regression analysis. Despite the significant effect of walking and waiting time on bus travel time, existing studies have not explicitly included in bus travel and arrival time predictions. This is mainly because collecting this data is not an easy task. As a result, these models can effectively evaluate the impact on bus travel time. One of the most important features of a public transport company is that the vehicle arrival times vary. Increasing passenger walking and waiting time reduces operational efficiency. Therefore, an undesirable situation arises for both the users and operators. It is important to consider walking time to estimate travel times on bus routes. A simple regression model for travel time modeling is presented. In addition to a travel time estimation model is developed considering walking times. Result showed that the simple regression model may be used to estimate the travel time by considering the waiting, walking time and the distance between the stops.

Declaration of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution Statement

B. Capali: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Draft writing – **H.Ceylan:** Conceptualization, Investigation, Supervision, Visualization, Review&Editing

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