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CASE STUDY AND APPLICATION

Transferability of a calibrated microscopic simulation model parameters for operational assessment of transit signal priority

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Abstract
This study evaluates the transferability of the calibrated parameters for mobility performance of transit signal priority (TSP) in a microscopic simulation environment. The analysis is based on two transit corridors in Florida. Two microscopic simulation VISSIM models, a base model, and a TSP model are developed for each corridor. The simulation models are calibrated to represent field conditions. Three driving behavior parameters that significantly affect the simulation results are identified and selected for the transferability study. A genetic algorithm technique is used to obtain an improved value for each of the three parameters for both transit corridors. Calibrated parameters obtained from the first study corridor, which maximize the correlation between simulated and field travel time, are used to estimate the second study corridor's travel time and compare the results to parameters optimized specifically for the second study corridor. The study uses the application-based and estimation-based approaches for the analysis. Overall, the TSP model parameter results are generally transferable between the two transit corridors. A percentage change of 9.25 and 18.50% are observed for two of the parameters between two TSP corridors which indicates that these two parameters are transferable. On the other hand, one of the parameters with a high percentage change value of 23.80% between the two TSP corridors are not transferable. The findings of this study may present key considerations for transportation agencies and practitioners when planning future TSP deployments.

Keywords Traffic microscopic simulation · Transferability · Transit signal priority · Calibrated parameters

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1 Introduction

Transit systems are the backbone of the transportation infrastructure, specifically in large cities (Chakroborty et al. 2001). The need to meet mobility, safety, and environmental objectives place greater demands on public transit systems (Covic and Voß 2019; Diab et al. 2021; Ge et al. 2021; Aemmer et al. 2022). Existing public transit systems must expand service regions, increase service frequency, and increase the efficiency to serve the growing needs of the public (Aemmer et al. 2022; Webb et al. 2020). Many large cities are experiencing an increase in traffic congestion, making existing transit system operations unreliable. Traffic congestion causes a significant increase in transit travel time and traffic delays (Kaeoruean et al. 2020). One potential cost-efficient strategy for improving transit service is to implement transit signal priority (TSP).

Transportation systems management and operations (TSM and O) strategies enhance the performance of existing transportation facilities to improve the mobility and ensure safety of the transportation system. Numerous studies have been conducted to evaluate the mobility and safety benefits of TSM and O strategies (Kodi et al. 2023; Alluri et al. 2020; Ali et al. 2022a; Kadeha et al. 2021; Haule et al. 2021; Kodi 2019; Kodi et al. 2021, 2022a, 2022b; Xiao et al. 2021). TSP is an operational strategy that facilitates the movement of transit vehicles (e.g., buses) through signalized intersections (Ali et al. 2022b, 2023; Mishra et al. 2020; Smith et al. 2005). TSP adjusts signal timing to reduce delays for public transit (Ahn and Rakha 2006; Ali et al. 2017, 2021b; Anderson and Daganzo 2019; Mishra et al. 2020; Skabardonis and Christofa 2011; Song et al. 2016; Zlatkovic et al. 2013; Ferreira et al., 2015).

It also extends the potential for a significant improvement in travel time reliability. In essence, it is expected that the provision of faster transit service may entice motorists to switch their travel modes to transit vehicles (Cesme et al. 2015; Consoli et al. 2015; Dion and Rakha 2005; Shaaban and Ghanim 2018; Zhou et al. 2006). TSP can also help to reduce operating costs and staffing requirements (Consoli et al. 2015). In addition, a decrease in bus travel times may permit a given level of service to be offered with fewer buses. However, it is difficult to conduct a TSP evaluation for all identified transit corridors. Therefore, transit agencies may prefer to transfer the results of an existing TSP corridor to a potential transit corridor, where TSP could be implemented in the future to provide better transit service.

Microsimulation is commonly used to evaluate the performance of various roadway facilities using a variety of performance measures, such as travel time, delay, and level of service (Ali et al. 2023; Kasubi et al. 2023). The operational performance of TSP is also often evaluated using microscopic simulation models (Ali et al. 2021a). This approach has several advantages. Traffic simulation offers the ability to represent various design and traffic operation options of roadway facilities and to evaluate their operational and safety performance before making any changes. Also, simulation models overcome the limitations of manually observing traffic operations. Of the commercially available microscopic simulation tools, VISSIM is typically used to evaluate the operational impacts of TSP. With increasingly more researchers beginning to rely on simulation as an important evaluation tool, simulation credibility is an essential concern. Several potential issues include whether these models accurately replicate realistic driver behavior and whether decisions made on the basis of the simulations can be trusted.

Microscopic simulation models contain several independent parameters that can be used to describe traffic flow characteristics, driver behavior, and traffic control operations. These models provide a default value for each parameter, but they also allow users to change the values to represent local traffic conditions (Park and Qi 2005). The process of adjusting and fine-tuning model parameters, using real-world data to realistically replicate local traffic conditions, is referred to as model calibration. In this study, transferability and calibration are uniquely interrelated. Microscopic simulation-based analyses are often performed with default parameter values or manually adjusted values. Rigorous calibration processes are often omitted, as they are time-consuming and require a vast amount of field data. Findings and conclusions based on uncalibrated or incorrectly calibrated models could be misleading and even incorrect. Hence, their proper calibration is a crucial step in simulation applications.

Since it is very difficult for transit agencies to determine whether implementing TSP on identified transit corridors will be beneficial, further research is needed to assist transit agencies in the evaluation process. Therefore, a microscopic simulation-based transferability study of TSP between two transit corridors is performed. Specifically, the objective of this study is to evaluate the transferability of the calibrated parameters for mobility performance of TSP between two existing transit corridors. Two transit corridors with TSP integration are developed in VISSIM using rigorous calibration procedures. To the best of the authors' knowledge, this is the first study to analyze the transferability of the calibrated parameters for the mobility performance of TSP.

2 Literature review

Several previous studies have examined the calibration and validation of microscopic simulation models for their use in traffic operation evaluation. However, there are no studies that investigated the transferability of calibrated parameters to evaluate the operational performance of TSP. Several studies have conducted transferability research on other topics that are not related to TSP. This research adopts the transferability methodology used in the previous studies (Bowman et al. 2017; Essa and Sayed 2015; Gallelli et al. 2017; Koppelman and Wilmot 1982; Sikder et al. 2014).

Essa and Sayed (2015) investigated the transferability of calibrated microsimulation model parameters for safety assessment using simulated conflicts. When applied to other sites, the authors examined whether the calibrated parameters gave reasonable results in terms of the correlation between the field-measured and the simulated conflicts at two signalized intersections. Calibrated VISSIM parameters obtained from the first intersection, which maximized the correlation between simulated and field-observed conflicts, were used to estimate traffic conflicts at the second intersection and compare the results to parameters optimized specifically for the second intersection. Results showed that the VISSIM parameters were generally transferable between the two locations, as the transferred parameters provided a better correlation between simulated and field-measured conflicts than using the default VISSIM parameters (Essa and Sayed 2015).

Gallelli et al. (2017) investigated the transferability of calibrated microsimulation parameters for an operational performance analysis of roundabouts. Transferability procedures were adopted to check whether calibrated parameters of one location were suitable for another location. The results showed that the application of Weidemann 99 parameters, calibrated for the first case study to the second case study, reduced the Root Mean Normalized Squared Error (RMNSE) by more than 50%, thus, confirming an acceptable level of transferability of these parameters between the two case studies.

Sikder et al. (2014) studied the spatial transferability of tour-based time-of-day choice models across different counties in the San Francisco Bay area in California (Sikder et al. 2014). Also tested was the hypothesis that pooling data from multiple geographic contexts helped in developing better transferability models than those estimated from a single context. An estimation-based approach yielded encouraging results in favor of transferability for the time-of-day choice model, with a majority of the parameters estimated in the pooled model found to be transferable (Sikder et al. 2014). The study also emphasized that pooling data from multiple geographic contexts appears to help in developing better transferability models with better transferability. However, attention was needed in selecting the geographic contexts from the latter in order to pool data.

Koppelman and Wilmot (1982) conducted a transferability analysis of disaggregate choice models. The study considered transferability from the perspective of the usefulness of the information provided by a model that predicts in a context different from that in which it is estimated. The study observed inconsistency between general measures of error that indicate whether transferability in this context was appropriate. Results also indicated that model transferability is a property of the estimation and application context, as well as the specification of the model. Transferability is also substantially improved by the adjustment of alternative specific constants (Koppelman and Wilmot 1982).

Bowman and Bradley (2017) examined the spatial transferability of an activity-based model (ABM), a travel forecasting model. Statistical tests were used to test transferability, including tests of regional differences in the model coefficients, likelihood ratio tests of model equivalence, and transferability indices, which measure the degree of model differences. Results indicated that parameters associated with travel time and cost caused the biggest problem with transferability. The study also concluded that agencies considering a transfer of an ABM from another region would do well to find a region within the same state (Bowman et al. 2017).

Despite the vast research on the transferability of various other transportation-related strategies, there are no studies on the transferability of the calibrated parameters for the mobility performance of TSP. Therefore, this study fills this gap in research by analyzing the transferability of the calibrated parameters for the mobility performance of TSP using application-based and estimation-based approaches for two transit corridors in Florida.

3 Study location and data

The study area and data required to estimate the transferability of the mobility performance of TSP are discussed in this section. The analysis was based on two arterial corridors, one in Jacksonville and another in Miami, Florida. The Jacksonville corridor is a 4-mile corridor along Mayport Road, between Wonderwood Drive and Atlantic Boulevard. This study corridor serves bus route #24, a major transit route in the area in both the Northbound (NB) and Southbound (SB) directions. The bus circulates between the Atlantic Village Shopping Center (SB) and the Wonderwood Park-n-Ride (NB). Figure 1 shows the Mayport Road study corridor with 10 signalized intersections. As shown in Fig. 1, the NB approach has a total of seven nearside, two farside, and eight mid-block bus stops, while the SB approach has six nearside, two farside, and four mid-block bus stops.

The Miami corridor is also a 4-mile corridor along SW 8th Street, between SW 107th Avenue and SW 67th Avenue, as shown in Fig. 2. The study corridor serves bus route #8, a major transit route in the area in both the Eastbound (EB) and Westbound (WB) directions. The bus circulates between the Florida International University (FIU) Terminal (WB) and the Brickell Station (EB). As shown in Fig. 2, the EB approach has a total of six nearside, two farside, and six mid-block bus stops, while the WB approach has three nearside, six farside, and four mid-block bus stops.

Various data were needed to conduct the transferability evaluation, including traffic flow data, geometric characteristics information, transit information, and signal timing data. Travel time and travel speed were extracted from the BlueToad™ paired devices for the Jacksonville corridor traffic flow data. BlueToad™ pairs are Bluetooth signal receivers which read the media access control (MAC) addresses of active Bluetooth devices in vehicles passing through their area of influence. Traffic count data were collected manually from video recordings. Travel time and travel speed were obtained from HERE Technologies and INRIX for the Miami corridor traffic flow data. HERE Technologies and INRIX are companies that provide location-based traffic data and analytics. HERE Technologies capture location content, such as road networks, traffic patterns, etc. Similarly, INRIX collects anonymized data on congestion, traffic incidents, etc. Traffic count data were obtained from the Florida Department of Transportation (FDOT) District 6.

For geometric characteristics, Google Maps and Google Earth Street View were used to verify certain roadway characteristics for both study corridors. Transit vehicle information considered while developing the VISSIM simulation models include bus route, bus stops, and bus schedule. These data were obtained from Jacksonville Transportation Authority's official website for the Jacksonville corridor (Jtafla 2021) and from the Miami-Dade County Transportation and Public Works official website for the Miami corridor (Miami-Dade Gov 2021).

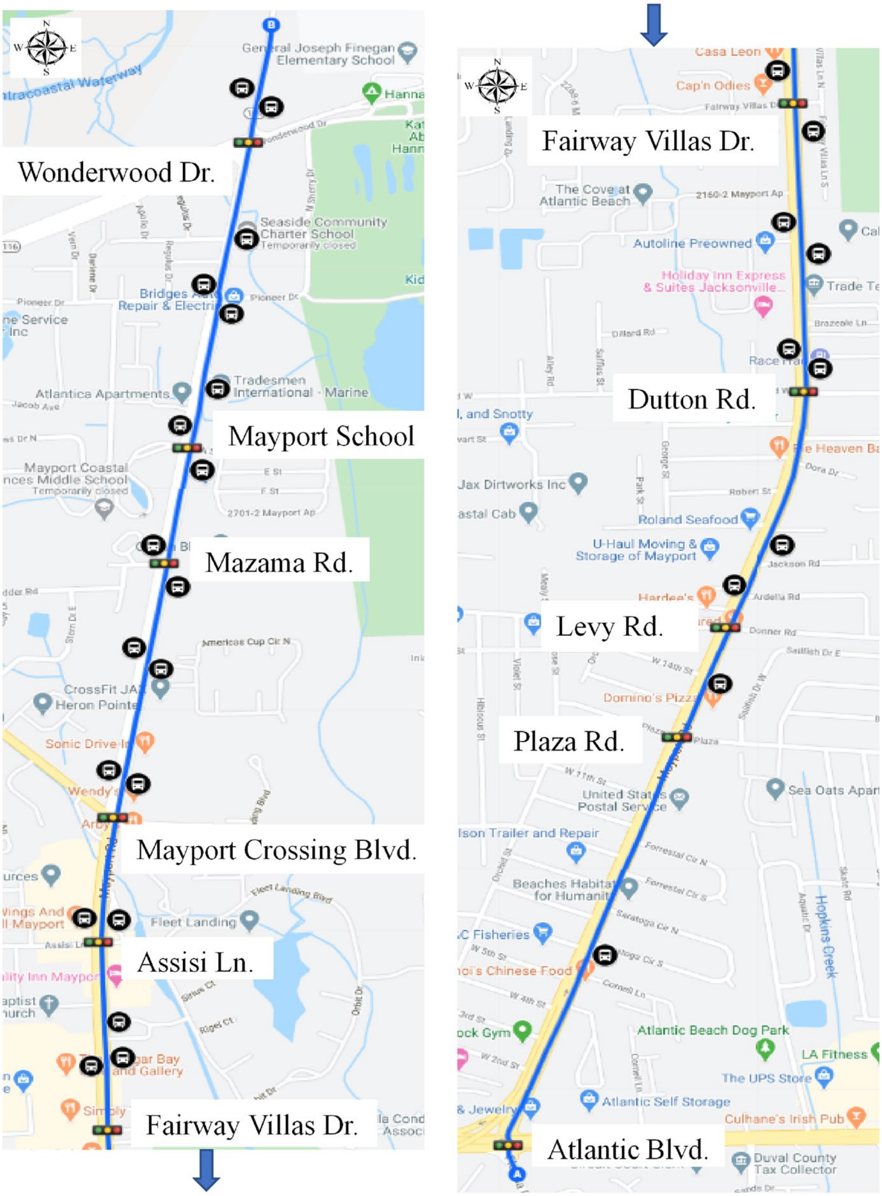


Fig. 1 Mayport Road study corridor in Jacksonville, Florida

For signal timing data, to replicate real-world traffic conditions in the VISSIM model, the actual signal timing data, i.e., green, yellow, and red intervals, turning movement counts, signal timing plans, signal split history, preemption logs, etc., for the evening peak period were collected. For the Jacksonville corridor, the data were obtained from FDOT District 2. The Miami-Dade County Traffic Signals

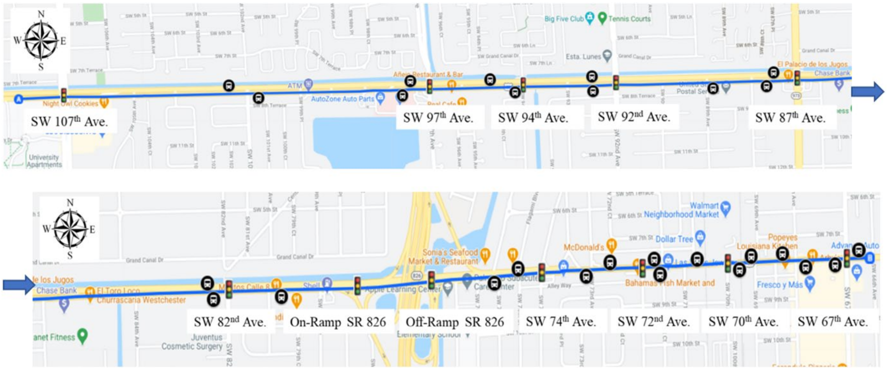


Fig. 2 SW 8th Street study corridor in Miami, Florida

and Signs Division and FDOT District 6 offices provided the data for the Miami corridor.

4 Methodology

To estimate the transferability of the mobility performance of TSP, the study explored the transferability of calibrated parameters in the microscopic simulation model (VISSIM) for operational analysis between two different study corridors (Mayport Road, in Jacksonville and SW 8th Street, in Miami). Specifically, the study investigated whether the transferred parameters of the TSP simulation model of the Mayport Road corridor produced reasonable results in terms of the relationship (correlation) between the field-measured travel time and the simulated travel time for the SW 8th Street TSP simulation model.

4.1 VISSIM simulation models

Two VISSIM microscopic simulation models (Base model and TSP model) were developed for both the Mayport Road corridor and the SW 8th Street corridor. The Base models were developed based on regular traffic operations, whereas the TSP model was developed with the TSP strategy integrated. The Base VISSIM model was developed to represent the base conditions, i.e., without TSP, by following the guidelines in the VISSIM manual and traffic analysis handbook (FDOT 2014). The analysis for both study corridors was conducted for the evening peak period (4:00 PM–7:00 PM) and was based on the existing network geometry, traffic, and transit operations. The analysis period was 3 h and 15 min, with the first 15 min used as the warm-up period.

To develop the Base VISSIM models, geometry information (e.g., number of lanes, lane widths, and turning radius) was first extracted and then drawn in technical drawings. All links and connectors were set using the actual field dimensions.

Detailed traffic counts were then defined in VISSIM using routes to represent all movements (i.e., left, right, and through) and traffic composition (i.e., percentage of cars, heavy vehicles, and buses). Public transit buses were defined using the number of buses per field conditions. Actual traffic signal settings were defined in VISSIM using the ring barrier controller (RBC). Integrated into the VISSIM software, the RBC interface allows users to simulate actuated control in a VISSIM model.

In the RBC, in addition to signal cycle length, the yellow time, red time, and the minimum and maximum green time of each phase were also defined. To represent the protected-permissive left turns, a detector was defined at each one of the four left-turn lanes for all approaches of a signalized intersection. Also, during a signal cycle, if the detector was occupied, a protected left-turn phase would be called by the RBC, otherwise, the left turn was permissive. Finally, a visual inspection was performed to ensure there were no abnormal movements of the simulated vehicles. The TSP scenario was then integrated into the base model to create the TSP model.

For the inclusion of the TSP operations along the same study corridors, the Base model was duplicated to create another microscopic simulation model where the TSP parameters were integrated into the signal groups (SGs) of the RBC in VISSIM. The RBC editor allows the user to set the timings used during the VISSIM simulation by the controller and stores these values in the external RBC data files with an ".rbc" file extension (PTV 2010). Programmable transit priority options for each transit SG are present in the signal controller. When a transit SG operates in a priority option in a priority mode, the SGs that conflict with the parent SGs of a transit SG can be abbreviated or omitted. For transit priority, the controller attempts to adjust its operation to give a green signal, i.e., either early green or extended green, to the transit SG by the time the transit vehicle arrives at the intersection.

4.2 Two-step VISSIM calibration process

Microscopic simulation models contain numerous independent parameters that can be used to describe traffic flow characteristics, traffic control operations, and driver behavior. These models provide a default value of each parameter; however, they also allow users to change the values to represent local traffic conditions. The microscopic simulation models need to be well calibrated to give reasonable and realistic results. In this study, the first calibration process matched the actual field conditions (desired speed and travel time) to ensure that VISSIM produced the field travel time. A second calibration step was performed to calibrate the identified VISSIM driving behavior parameters.

4.2.1 First calibration process

The primary goal of the first calibration process was to determine if the simulated travel time in VISSIM was similar to the field travel time. To better calibrate the travel time, the desired speeds were calibrated to match the field conditions. For the desired speed, the cumulative distribution curve for the microscopic simulation VISSIM model was also modified to match the field conditions. The coefficient of determination (R^2) was calculated to assess the resemblance between the simulation and the field conditions. The value of R^2 was found to be 0.81 and 0.84 for the Mayport Road corridor and SW 8th Street corridor, respectively. The Geoffrey E. Havers (GEH) empirical formula was also used as the acceptance criteria for the model and set as GEH < 5.0 for at least 85% of intersections (FDOT 2014). The GEH empirical formula that was used as the acceptance criteria for the model is:

$$GEH = \sqrt{\frac{2(M - C)^2}{M + C}} \tag{1}$$

where, M is the traffic volume from the traffic simulation model, and C is the real-world traffic count in vehicles per hour. The acceptance criteria was that the GEH < 5.0 for at least 85% of the intersections. Based on our analysis, from the calibration results, a GEH < 5.0 was observed for 89 and 92% of the intersections in the model for the Mayport Road corridor and SW 8th Street corridor, respectively.

4.2.2 The required number of VISSIM simulation runs

To replicate the stochasticity of traffic flow, VISSIM assigns different random seeds for each run. Random seeding returns different outputs for each run and effects parameters, such as when a vehicle enters the network, which lane to use, the aggressiveness level of the driver, and interaction between vehicles (Radwan et al. 2009). VISSIM does not automatically calculate the required number of runs necessary to achieve good results that are within the tolerable error range. Therefore, the number of runs was determined by using the Traffic Analysis handbook formula:

$$n = \left(\frac{s \times t_{\alpha/2}}{\mu \times \epsilon}\right)^2 \tag{2}$$

where n = the required number of simulation runs, s = the standard deviation of the system performance measure based on the the previous simulation runs, $t_{\alpha/2}$ = the critical value of a two-sided Student t-statistic at the confidence level of α nd n − 1 degree of freedom (df), μ = the mean of the system performance measure, and ϵ = the tolerable error, specified as a fraction of μ, desirable value of 10%.

To reduce the impact of the stochastic nature of the model on the results, the simulation model was run with different random number seeds. Note that the formula in Eq. 2 considers the standard deviation, the 95% confidence interval, the mean, and the tolerable error of 10%. Travel speed was used as the performance measure to determine the number of simulation runs. A total of 17 and 15 simulation runs were determined for the Mayport Road corridor and SW 8th Street corridor, respectively.

4.2.3 Second calibration process

The main goal of the second calibration process was to enhance the correlation between the simulated travel time and the field travel time by calibrating the VISSIM parameters. The most critical VISSIM parameters, which had a significant effect on

Table 1 Maximum and minimum values of the VISSIM parameters along with range

#	Parameter	Default	Range
Car-following parameters			
1	Average standstill distance (w74ax)	2.00 (m)	> 1 (m)
2	Additive part of safety distance (w74bxAdd)	2.00 (m)	1 to 5.00 (m)
3	Multiplicative part of safety distance (w74bxMult)	3.00 (m)	1.00 to 6.00 (m)
Lane change parameters			
4	Lane change	656.2 ft.	> 656.2 ft.
5	Emergency stop	16.4 ft.	As per field observations

m meters, *ft.* feet; parentheses refer to parameter identifiers in VISSIM.

the simulation results, were identified, as shown in Table 1. The default values and range of the values of the VISSIM parameters are also provided in Table 1. Since the Wiedemann 74 model is more suitable for urban traffic and merging areas, this model was used instead of the Wiedemann 99 model, which is more suitable for freeway traffic with no merging areas (PTV 2010). Subsequently, a genetic algorithm technique was applied to estimate the optimized values of the identified parameters.

The *average standstill distance* is the average desired distance between two cars (PTV 2010). The tolerance lies from − 1.0 m to + 1.0 m, which is normally distributed around 0.0 m, with a standard deviation of 0.3 m. The default value is 2.0 m (6.56 feet). The *additive part of the safety distance* value, used for the computation of the desired safety distance (PTV 2010), allows the time requirement values to be adjusted, and the default value is also 2.0 m (6.56 feet). The *multiplicative part of the safety distance* value, used for computation of the desired safety distance (PTV 2010), also allows the time requirement values to be adjusted. A greater value reflects a greater distribution (i.e., standard deviation) of safety distance. The default value is 3.0 m (9.84 feet).

For the lane changing parameters, *lane change* was used to model the lane change rule for vehicles that follow their route or in a dynamic assignment, their path (PTV 2010). The lane change rule applies to the distance before the connector from which those vehicles whose route or path leads across the connector, try to choose the lane in which they reach the connector without changing lanes. The standard value is 200 m (i.e., 565 feet and 2.016 inches), and the minimum value is 10 m (i.e., 32 feet and 9.701 inches). The lane change value must be > = *Emergency Stop* + 5.0 m (i.e., 16 feet and 4.85 inches).

Emergency Stop is used to model the lane change rule of vehicles that follow their route, or in the dynamic assignment, their path, and the default value is a minimum of 5.0 m (PTV 2010). If the lanes cannot be reached before the connector at the emergency stop position, the vehicle stops and waits for a sufficiently large enough gap. The system measures upstream, starting from the beginning of the connector. When a vehicle has to make more than one lane change, 5.0 m per lane is also taken into account in each case. If the current lane has an odd number, 2.5 m are also added to the total length of the emergency stop distance. This prevents a conflict from occurring in the case of two vehicles with identical positions that are set to change lanes on neighboring lanes.

Due to the uniqueness of the geometry of the signalized intersections along the corridor, there was no definite value for lane change and emergency stop parameters. The value of the lane changing parameters differed as per the geometry and traffic pattern along the corridor. Therefore, the genetic algorithm (GA) technique was performed only for the VISSIM car following parameters.

4.2.4 Genetic algorithm technique

After identifying the VISSIM car following parameters and their acceptable ranges, a GA process was used to calibrate and optimize the values of the selected parameters (Park and Qi 2005). A GA analysis is a heuristic optimization technique based on the mechanics of natural selection and evolution. It works with a population of individuals, each of which represents a possible solution to a given problem. The GA procedure was applied to find the best values of the selected parameters which gave the highest correlation between the simulated and field-measured travel times. The basic operators of the GA, i.e., reproduction, crossover, mutation, and elitism, were used to generate the next generation.

The reproduction operator selects individuals with higher fitness. The crossover operator creates the next population from the intermediate population, and the mutation operator was used to explore areas that have not been searched. The initial population was created randomly, which means that all solutions have an equal chance to fall into the population. However, random selection does not guarantee the uniform coverage of each parameter space. Therefore, a latin hypercube sampling method (LHS) was used to select the initial population. The relative error of the average travel time between the simulation output and field data was used as the fitness value of the GA. The fitness function is represented by the following equation:

$$FV = \frac{|TT\,field - TT\,simulation|}{TT\,field} \tag{3}$$

where, FV = is the fitness value, $TTfield$ = the average travel time from the field, and $TTsimulation$ = the average travel time from the simulation.

The automation access of VISSIM was completed using the VISSIM component object model (COM) interface that enables users to access VISSIM through many scripting languages. However, the VISSIM COM interface does not cover all of the VISSIM parameters selected for the study. To overcome this challenge, all parameter values were set to automatically change each time by editing the text contents in the VISSIM input (*.inp) files.

4.3 Transferability assessment approaches

Transferability assessment was conducted using two approaches: (a) the application-based approach and (b) the estimation-based approach (Bowman et al. 2017; Essa and Sayed 2015; Gallelli et al. 2017; Koppelman and Wilmot 1982; Sikder et al. 2014). Each approach is discussed in the following subsections.

4.3.1 Application-based approach

In the application-based approach, the model parameters were calibrated using data from one location (the base context (i.e., Mayport Road Corridor) and applied directly, with no change to the data, to the second location (the application context (i.e., SW 8th Street Corridor) to assess how well the calibrated TSP model predicts in the other location (i.e., SW 8th Street Corridor). This approach is more direct and generally tests the transferability of the model as a whole without examining which specific parameters are transferable.

4.3.2 Estimation-based approach

In the estimation-based approach, the TSP simulation model parameters were calibrated using data from one location (i.e., Mayport Road Corridor) and recalibrated using data from the second location (i.e., SW 8th Street Corridor). Model transferability was determined by identifying whether the calibrated parameter values were different between the two TSP corridor locations. This approach was more comprehensive, as it can test whether each and every parameter in a model was transferable.

4.4 Microscopic simulation parameters transferability

To avoid any influence of a random component or a lucky parameters' combination on the outcomes of the transferability approach, both the application-based and the estimation-based approaches were used. Specifically, according to the application-based approach, the calibrated parameters of the TSP model obtained using data from the first location (i.e., Mayport Road Corridor) were applied for the simulation of the second TSP location (i.e., SW 8th Street Corridor). For the estimation-based approach, the calibration process was applied also using the first location (i.e., Mayport Road Corridor) dataset and again recalibrated using the second location dataset (i.e., SW 8th Street Corridor). The methodology was comprised of four scenarios to determine the correlation between field and simulated conditions.

4.4.1 Transferability assessment exploration scenarios

Scenario 1 (without any calibration process): In this scenario, the second TSP location (i.e., SW 8th Street Corridor) was modeled and simulated using default VISSIM values without any calibration. The correlation between field-measured and simulated travel time was estimated.

Scenario 2 (with only the first calibration process): In this scenario, the second TSP location (i.e., SW 8th Street Corridor) was simulated, and only the first calibration process was used. With the driving behavior parameters set at default values, the correlation between field-measured and simulated travel time was estimated.

Scenario 3 (application-based approach): In this scenario, the second TSP location (i.e., SW 8th Street Corridor) was simulated using the first calibration process (i.e., only the values of desired speeds for the Mayport Road Corridor). The values of the second calibration process of the first TSP location (i.e., Mayport Road Corridor) were also directly transferred. The values were directly transferred, without any recalibration, as per the application-based approach to estimate the correlation between field-measured and simulated travel time.

Scenario 4 (estimation-based approach): Considering the estimation-based approach, the Wiedemann 74 significant factors (driving behavior parameters), calibrated for the second TSP location (i.e., SW 8th Street Corridor), were compared with the same parameters calibrated for the first TSP location (i.e., Mayport Road Corridor) to evaluate the degree of transferability. In other words, the second TSP location (i.e., SW 8th Street Corridor) was simulated using the values of the first and the second calibration process for the first TSP location (i.e., Mayport Road Corridor). The values were directly transferred, and a recalibration process for the local condition was also executed using the estimation-based approach.

4.5 Transferability of individual parameters

To further examine the transferability of the VISSIM calibrated parameters, the transferability of each parameter of the TSP VISSIM models was investigated by comparing the calibrated values between the two locations. The calibrated values were the results of the GA procedure for both study locations. The percentage change for each parameter was determined by Eq. 4.

$$\%\ of\ change = \frac{V1 - V2}{X1 - X2} \times 100 \tag{4}$$

where, $V1$ = the calibrated value of the parameter from the first TSP study location (i.e., Mayport Road Corridor), $V2$ = the calibrated value of the parameter from the second TSP study location (i.e., SW 8th Street Corridor), $X1$ = the maximum value of the parameter and $X2$ = the minimum value of the parameter.

The maximum and minimum values of the parameters were assumed based on the information listed in the VISSIM User Manual (Park and Qi 2005; PTV 2010).

5 Results and discussions

The following subsections discuss the transferability analysis results for the TSP simulation model, the four simulation scenarios, and the transferability of individual TSP integrated simulation model parameters.

5.1 Transferability investigation of simulation model

The data from the Mayport Road TSP corridor in Jacksonville was used to investigate the transferability for the SW 8th Street corridor in Miami. The correlation between simulated and field travel time was calculated for the TSP VISSIM model for the SW 8th Street corridor for four scenarios.

For the first scenario, the default values of the VISSIM driving behavior parameters were used for the SW 8th Street TSP corridor. In the second scenario, only the first calibration process was applied, and the default values of the VISSIM parameters were used for the SW 8th Street TSP corridor. In the third scenario, the SW 8th Street TSP corridor was simulated using the directly transferred calibrated values from the Mayport Road TSP corridor. Finally, in the fourth scenario, the SW 8th Street TSP corridor was simulated using the directly transferred calibrated values from the Mayport Road TSP corridor, and also, the SW 8th Street TSP corridor was recalibrated as per local conditions. Table 2 summarizes the values used for the TSP VISSIM parameters and which calibration process was applied.

5.1.1 Scenario 1—without any calibration process

In Scenario 1, the default VISSIM parameters were used to model the SW 8th Street TSP corridor in Miami without the first and second calibration processes, and the correlation between field and simulated travel time was estimated. The results, illustrated in Fig. 3, revealed that using the default values of the VISSIM parameters, the field and simulated travel time were not correlated. Thus, using simulation models without proper calibration can lead to subjective results and should be avoided.

Table 2 Four scenarios of SW 8th Street for transferability investigation

Scenario	VISSIM Parameters			Description	First calibration process	Second calibration process
	W74ax	W74bxAdd	W74bx Mult			
1	2.0	2.0	3.0	Default	No	No
2	2.0	2.0	3.0	Default	Yes	No
3	3.82	4.97	5.74	Application-based	Yes	No
4	3.45	4.23	4.55	Estimation-based	Yes	Yes

W74ax average standstill distance, *W74bxAdd* additive part of safety distance, *W74bxMult* multiplicative part of safety distance

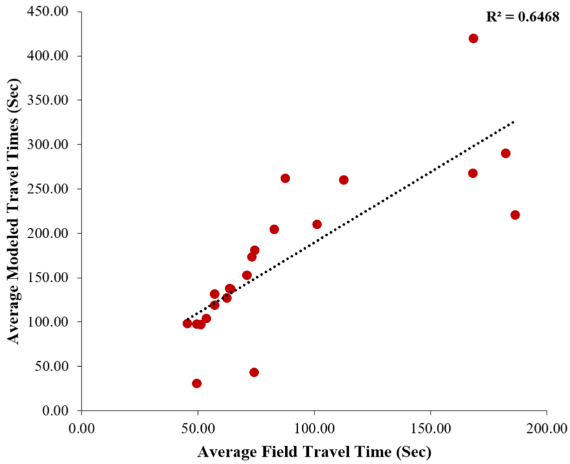


Fig. 3 Result of scenario 1

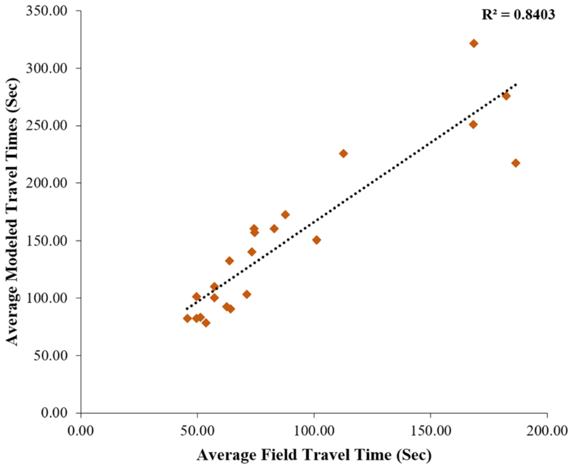
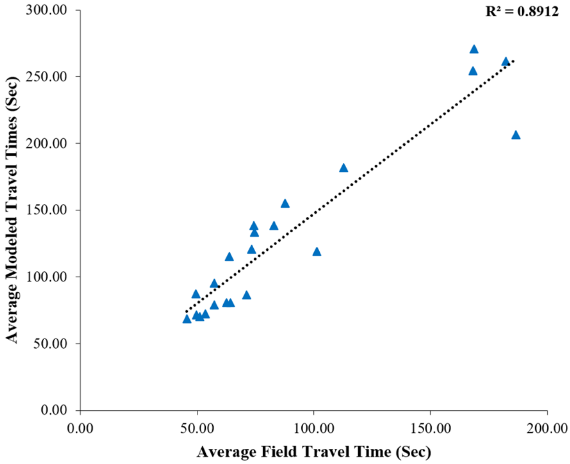


Fig. 4 Result of scenario 2

5.1.2 Scenario 2—with only the first calibration process

In Scenario 2, the SW 8th Street TSP corridor was simulated using only the first calibration process to estimate the correlation between field and simulated travel time. The results, illustrated in Fig. 4, showed improvement in the correlation between field and simulated travel time compared to Scenario 1. This result significantly emphasized the need and importance of the first calibration process to match the travel time, where the desired speeds were also matched. For the desired speeds, the cumulative distribution curve of the TSP VISSIM model was modified as per field conditions. Better results could be realized if the default driver behavior, simulated by the Wiedemann 74 car following model in VISSIM, was also calibrated.

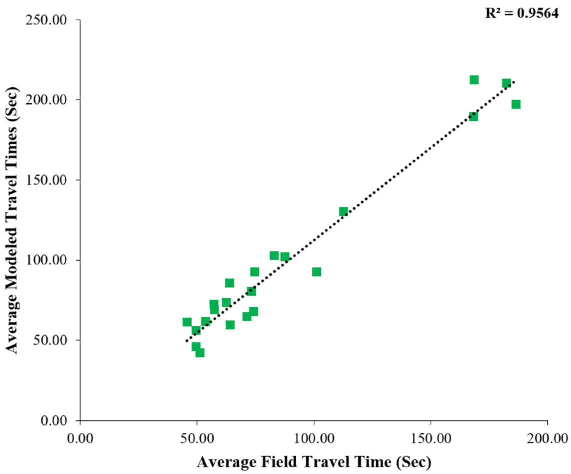
Fig. 5 Result of scenario 3



5.1.3 Scenario 3—application-based approach

In Scenario 3, the SW 8th Street TSP corridor was simulated using the desired speeds from the Mayport Road TSP corridor as a part of the first calibration process. The values of the second calibration process for the Mayport Road TSP corridor were also directly transferred to the SW 8th Street TSP simulation model, according to the application-based approach, to estimate the correlation between field and simulated travel time. The results, illustrated in Fig. 5, showed that the correlation between field and simulated travel time was enhanced when the transferred values of the parameters were used instead of the default values. This finding confirms that the main VISSIM parameters of a TSP simulation model that affect travel time are transferable for use at similar, or close to similar, corridors. Thus, the results reveal

Fig. 6 Result of scenario 4



an acceptable level of transferability of the Wiedemann 74 driving behavior parameters between the two TSP study corridors.

5.1.4 Scenario 4—estimation-based Approach

In Scenario 4, the SW 8th Street TSP corridor was simulated using the desired speeds from the Mayport Road TSP corridor as a part of the first calibration process. Also, the values of the second calibration process of the Mayport Road TSP corridor were directly transferred to the SW 8th Street TSP simulation model. Per the estimation-based process, the SW 8th Street TSP corridor was recalibrated for local conditions by following both the first and second calibration processes. The results, illustrated in Fig. 6, showed the correlation between field and simulated travel time was higher for Scenario 4 than in all other scenarios. This enhancement in correlation was expected due to the local calibration process. The difference between Scenario 3 and Scenario 4 was evident. Therefore, although local calibration of the model parameters was crucial, using calibrated parameters transferred from similar or close to similar corridors can lead to good results. The next section discusses the transferability of individual parameters used in the estimation-based approach.

5.2 Transferability results of individual parameters

Table 3 shows the transferability results of individual parameters. As shown in Table 3, when the calibration process was applied for both TSP corridors, the parameter ‘W7ax’ had a percentage change of 9.25%, a low value of change, which signifies that the parameter was transferable. For the ‘W74bxAdd’ parameter, a percentage change of 18.50% was observed, which signifies that the parameter was also transferable to some degree (Essa and Sayed 2015). However, for the ‘W74bxMult’ parameter, a higher percentage change (23.80%) was observed. This high change indicates that this parameter was not transferable between the two TSP corridors and needs a new calibration to enhance the results (Essa and Sayed 2015).

Model transferability of the two TSP corridors was assessed using two different approaches: (a) the application-based approach and (b) the estimation-based approach. The application-based approach tests the transferability of a model as a whole, while the estimation-based approach tests the transferability of each

Table 3 Results of transferability of individual parameters

Parameter		Calibrated value		Difference	Percent change (%)
No.	Name	Mayport Road Corridor	SW 8th Street Corridor		
1.	W74ax	3.82	3.45	0.37	09.25
2.	W74bxAdd	4.97	4.23	0.74	18.50
3.	W74bxMult	5.75	4.55	1.20	23.80

W74ax average standstill distance, *W74bxAdd* additive part of safety distance, *W74bxMult* multiplicative part of safety distance parameter. Based on the assessment of the two approaches, the estimation-based approach was observed to be more comprehensive, as it exhibited better transferability with respect to all parameters for the two TSP corridors.

6 Conclusions

A microscopic simulation approach was used to evaluate the transferability of the calibrated parameters for the mobility performance of TSP between two transit corridors. The two transit corridors studied were Mayport Road in Jacksonville, Florida, and SW 8th Street in Miami, Florida. Specifically, the study investigated whether the results of the calibrated parameters for the Mayport Road TSP corridor were transferable to the SW 8th Street TSP corridor. The two transit corridors with TSP integration were developed in VISSIM after undergoing rigorous calibration procedures. In this study, a two-step VISSIM calibration process was adopted. The first calibration process matched the actual field conditions (i.e., desired speed and travel time) to ensure that VISSIM produced field travel time. The second calibration process was performed to calibrate the identified VISSIM driving behavior parameters. The calibrated value of the VISSIM driving behavior parameters was obtained using a genetic algorithm technique.

The calibrated parameters were utilized to evaluate the transferability of the mobility performance of TSP between the two transit corridors. This study fills a gap in existing research by analyzing the transferability of the calibrated parameters for the mobility performance of TSP, using the application and estimation-based approaches. Also, the study proposed and assessed four transferability exploration scenarios. Findings for the four scenarios include:

- In Scenario 1, the SW 8th Street corridor was modeled and simulated using the default values without any calibration. The R^2 value was 0.6468, indicating that the field-measured and simulated travel times were not correlated.
- In Scenario 2, the SW 8th Street corridor was simulated, and only the first calibration process was used. The R^2 value was 0.8403, revealing the importance of the first calibration step and also indicating that the correlation between field-measured and simulated travel time improved.
- In Scenario 3, the SW 8th Street corridor was simulated using the transferred values of the first and second calibration process of the Mayport Road corridor as a part of the application-based approach. The R^2 value was 0.8912, indicating a better correlation between field-measured and simulated travel time. Moreover, findings from the application-based approach confirmed that the main VISSIM parameters that affect travel time are transferable for use on similar corridors. The results also revealed an acceptable level of transferability.
- In Scenario 4, the SW 8th Street corridor was simulated using the transferred values of the first and second calibration process of the Mayport Road corridor and then recalibrated with local conditions to conduct an estimation-based analysis. The R^2 value was 0.9564, indicating the best correlation between field-measured and simulated travel time compared to all other scenarios.

The transferability of individual parameters was also investigated using the estimation-based approach. After both calibration processes were applied to the two TSP transit corridors, the difference in the calibrated values for the average standstill distance, the additive part of the safety distance, and the multiplicative part of the safety distance were 0.37, 0.74, and 1.20, respectively. The percentage change between both corridors in terms of the average standstill distance was 09.25%. This low percentage change value signifies that this parameter is transferable. The percentage change between both corridors in terms of the additive part of the safety distance was 18.50%, signifying that this parameter is transferable to some degree (Essa and Sayed 2015). Finally, the percentage change between both corridors in terms of the multiplicative part of the safety distance was 23.80%, signifying that this parameter is not transferable. The findings of this study may present key considerations for transportation agencies and practitioners when planning future TSP deployments.

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