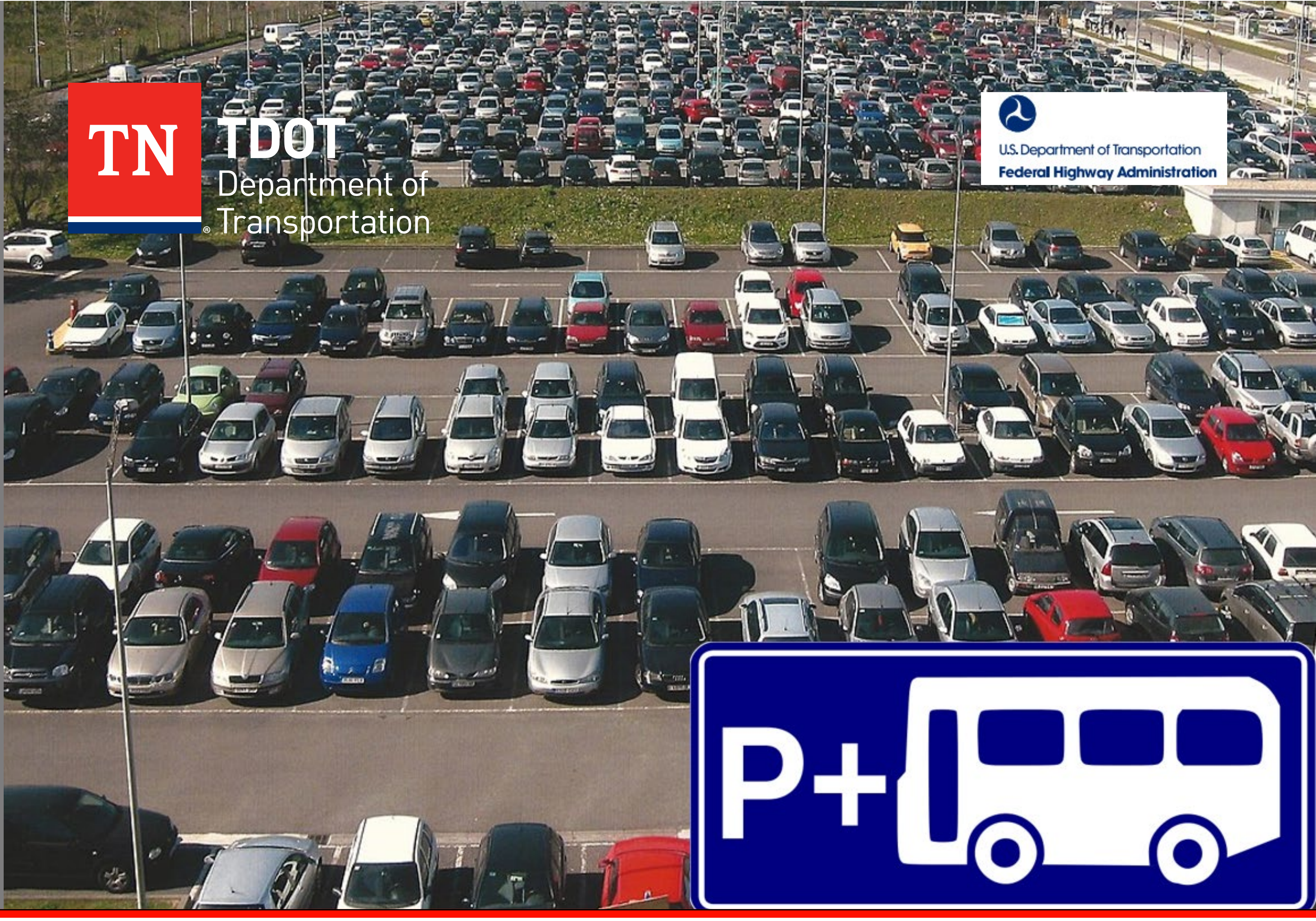

TN TDOT Department of Transportation

U.S. Department of Transportation Federal Highway Administration

Improvement of Park-and-Ride Facilities and Services in Metropolitan Areas of Tennessee

OPTIMAL PLACEMENT OF PARK-AND-RIDE FACILITIES

Research Final Report from University of Tennessee, Knoxville | Anahita Khojandi, Candace Brakewood, Christopher Cherry, Mingzhou Jin, Shahrbanoo Rezaei, Antora Mohsena Haque | June 25, 2021

Sponsored by Tennessee Department of Transportation Long Range Planning

Research Office & Federal Highway Administration

DISCLAIMER

This research was funded through the State Planning and Research (SPR) Program by the Tennessee Department of Transportation and the Federal Highway Administration under ***RES2020-15: Improvement of Park-and-Ride Facilities and Services in Metropolitan Areas of Tennessee.***

This document is disseminated under the sponsorship of the Tennessee Department of Transportation and the United States Department of Transportation in the interest of information exchange. The State of Tennessee and the United States Government assume no liability of its contents or use thereof.

The contents of this report reflect the views of the author(s) who are solely responsible for the facts and accuracy of the material presented. The contents do not necessarily reflect the official views of the Tennessee Department of Transportation or the United States Department of Transportation.

Technical Report Documentation Page

1. Report No. RES2020-15	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle *Improvement of Park-and-Ride Facilities and Services in Metropolitan Areas of Tennessee*		5. Report Date 25 June 2021 6. Performing Organization Code
7. Author(s) Anahita Khojandi, Candace Brakewood, Christopher Cherry, Mingzhou Jin, Shahrbanoo Rezaei, Antora Mohsena Haque		8. Performing Organization Report No.
9. Performing Organization Name and Address The University of Tennessee, Knoxville 521 John D. Tickle Building Knoxville, TN 37996-0700		10. Work Unit No. (TRAIS) 11. Contract or Grant No. Contract RES2020-15
12. Sponsoring Agency Name and Address Tennessee Department of Transportation 505 Deaderick Street, Suite 900 Nashville, TN 37243		13. Type of Report and Period Covered Final Report August 2018 - June 2021 14. Sponsoring Agency Code
15. Supplementary Notes Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration.		

16. Abstract

Strategic placement of park-and-ride (P&R) facilities is extremely important to ensure the facilities are effectively utilized by commuters, avoiding oversubscription or underutilization after placement. This report develops a framework that integrates a demand model and an optimization model to study the optimal placement of P&R facilities to maximize the total number of commuters who switch from single occupancy vehicles (SOVs) to public transit. The models and results are presented through a case study for the City of Nashville, a major metropolitan area in the State of Tennessee, US. The framework first develops a P&R demand model through a discrete choice model, specifically the multinomial logit model, to characterize the mode choice behavior of individuals in a multimodal network. Next, it leverages the estimated proportion of commuters that are expected to switch to P&Rs from alternatives in a mixed integer linear programming (MILP) optimization model to prescribe the optimal locations of P&R facilities. Model calibration is performed using the literature and available data. The results of the case study are then presented and sensitivity analysis is performed to provide further insights. Finally, an analysis is performed to examine the potential benefits of replacing the P&R facilities with transit-oriented developments (TODs). The results of the case study suggest that the optimal placement of P&R facilities has the potential to improve the network performance and reduce emission. In addition, in this particular case study, P&R facilities generally remain more favorable compared with TODs.

17. Key Words **PARK-AND-RIDE, TRANSIT ORIENTED DEVELOPMENTS (TOD), FACILITY LOCATION PLANNING, OPTIMIZATION MODEL, LOGIT MODEL**		18. Distribution Statement No restriction. This document is available to the public from the sponsoring agency at the website https://www.tn.gov/	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages	22. Price

Acknowledgement

To date, this project has partially supported the creation of three manuscripts, two of which are already accepted for publication and the other one is currently under preparation:

- Haque, A., C. Brakewood, S. Rezaei, A. Khojandi. A Literature Review on Park-and-Rides, *Journal of Transport and Land Use,* DOI: 10.5198/jtlu.2021.1923 (forthcoming).
- Rezaei, S., A. Khojandi, A. Haque, C. Brakewood, M. Jin, C. Cherry. Performance Evaluation of Mode Choice Models Under Balanced and Imbalanced Data Assumptions. *Transportation Letters: the International Journal of Transportation Research*, DOI: 10.1080/19427867.2021.1955567 (forthcoming).
- Rezaei, S., A. Khojandi, A. Haque, C. Brakewood, M. Jin, C. Cherry. Park-and-Ride Facility Location Optimization: A Case Study for Nashville, Tennessee (under preparation).

Executive Summary

Strategic placement of park-and-ride (P&R) facilities can encourage the use of public transit and non-motorized transportation modes for commuting. As a result, it has the potential to mitigate many negative externalities related to automotive transportation including traffic congestion, parking shortages in highly-populated areas, and greenhouse gas emissions, among others. It is, however, important to account for many considerations when selecting sites to host P&R facilities to assure that the facilities will be effectively utilized by commuters, avoiding oversubscription or underutilization after placement. In addition, transit is mostly used by commuters who walk to stations. Therefore, it is also important to understand pros and cons of transit-oriented developments (TODs), which are compact, mixed use developments near transit facilities and have generally high-quality walking environments.

Tennessee Department of Transportation (TDOT) is aspired to improve the transportation system of Tennessee and one of TDOT's important endeavors is to improve Tennessee's P&R network. Hence, the purpose of this report was to conduct a comprehensive investigation on P&R facilities and services, as well as TODs, to improve the P&R network in the State of Tennessee, to ultimately encourage the use of public transit and non-motorized transportation modes for commuting and mitigate many negative externalities related to automotive transportation. As such, the contributions of this report are twofold:

(1) Conduct literature review to identify the best practices in design and development of P&R facilities and TODs.

(2) Determine the optimal locations and sizes of P&R facilities/TODs among a set of candidate locations to improve the network.

A review was conducted to examine the literature on P&R facilities and TODs. Various themes were identified for P&Rs. In addition, TOD best practices and legislation, planning, and policy documents for Nashville, Tennessee, and its peer cities were surveyed. The review pointed to important guidelines and best practices, methodologies for understanding commuters' behavior towards P&Rs, rigorous approaches for optimal planning of P&Rs and evaluating the P&R network, various considerations regarding utilization of P&Rs, and their comparisons to TODs. The findings from this review were then leveraged to develop a holistic framework to prescribe the placement of P&R facilities/TODs among a set of candidate locations to improve the network.

A framework was developed to integrate a demand model and an optimization model to study the optimal placement of P&R facilities to maximize the total number of commuters who switch from single occupancy vehicles (SOVs) to public transit. The framework first developed a P&R demand model through a discrete choice model, specifically the multinomial logit model, to characterize the mode choice behavior of individuals in a multimodal network. Next, it used the estimated proportion of commuters that are expected to switch to P&Rs from alternatives in a mixed integer linear programming (MILP) optimization model to prescribe the optimal locations of P&R facilities.

A case study was performed for the City of Nashville, a major metropolitan area in Tennessee. Model calibration was performed using the literature and data, provided by the Metropolitan Planning Organization (MPO). The data included daily trips in Davidson county, and six of its surrounding counties, namely Maury, Williamson, Sumner, Rutherford, Robertson and Wilson. These trips were carried by SOVs, high occupancy vehicles (HOVs) and transit. As such, one major limitation was the paucity of data on the P&R mode.

In the case study, 14 existing P&Rs and 11 candidate P&Rs were considered. The proposed MILP model was able to successfully identify reasonable sets of candidate locations to meet the specified constraints, given two objective functions of P&R utilization maximization and emission reduction. In addition, the model enabled examining the benefits of replacing existing P&Rs with candidate P&Rs. Sensitivity analysis was conducted to evaluate the sensitivity of the results with respect to the estimated parameters. The results showed that although the model was rather robust, the parameter choices could indeed impact the final recommendations of the model.

Finally, the potential use of TODs in this network was examined. Specifically, TODs and P&Rs were compared to determine whether replacing a P&R facility with a TOD would reduce the vehicle kilometer traveled (VKT). The analysis was performed in four steps: First, the average VKT reduction per P&R round trip in each P&R station was estimated. Next, because P&R and TOD compete for land area, the estimated VKT reduction was transformed to average VKT reduction per P&R land hectare. Then the VKT reduction for TOD in each station was estimated. Finally, the characteristics of TODs (residential density and average VKT reduction per household) were identified that allowed them to meet the average VKT reduction per P&R land hectare in each station. These characteristics were consequently evaluated for feasibility. The results suggested that, in this case study in which the candidate locations were particularly identified for potential P&R facilities, it was generally favorable to use the facilities for P&Rs instead of TODs. However, this does not imply that candidate locations for TODs may not exist. Further research is needed to identify ideal candidate locations for TODs.

Key Findings

- Despite having general guidelines for the entire US context from Transit Cooperative Research Program (TCRP) reports, State DOT based P&R development guidelines varied across states, suggesting the need for state-specific guidelines.
- Data availability (quantity and format) proved to be key to large-scale modeling and quality model calibration.
- The optimal set of candidate locations prescribed by the optimization model varied as a result of the choice of objective function, constraints, and model parameters.
- Given the available data, P&R facilities generally remained more favorable compared with TODs in the City of Nashville.

Key Recommendations

- More P&R-based research should be conducted on bus-based P&Rs and in areas with less extensive transit services.
- Surveys focusing on P&R facilities and their alternatives should be conducted in the City of Nashville to get accurate and reliable demand model for all modes, especially for P&Rs.
- A rich dataset including ‘travel cost,’ ‘parking fare,’ ‘transit frequency,’ and ‘waiting time,’ among others, should be collected to allow for developing a more accurate and comprehensive demand model.

- In case of imbalanced data, balancing techniques must be leveraged to improve the prediction performance of the demand model across all modes.
- Appropriate candidate locations must be selected to be included in the optimization model. Consequently, the objective function and model constraints must be clearly identified before executing the optimization model to obtain the recommendations.
- Feasible range of TOD characteristics must be clearly defined to enable a meaningful comparison between P&Rs and TODs and ensure actionable decisions regarding the placement of TODs in the network.

Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

> *P&R site selection is extremely important to ensure that all facilities in a system will be effectively utilized by commuters, avoiding oversubscription or underutilization after placement.*

One of the most important problems that large cities around the world are faced with is severe traffic congestion, which is caused by increasing car ownership and use. In order to mitigate the congestion problems, park-and-ride (P&R) facilities have been introduced as an effective approach. P&R facilities provide commuters with the option to reach to the central business district (CBD), generally the most congested area in a city, by the public transportation, such as bus, rail system (rapid transit, light rail, or commuter rail), or carpool. P&R systems follow a simple model, where private vehicle owners use their vehicles to travel from their origin to the facility, park their cars in the facility, and then use public transportation to get to their final destination. In other words, commuters are allowed to use their private cars in the least congested portion of the trip to reach the P&R facility and then use the effective public transportation services to continue their journey to the most congested area (Song, He, & Zhang, 2017).

Since the first introduction of P&R in Detroit in the 1930s, it has been recognized as an efficient approach to promote public transportation and mitigate negative traffic externalities in urban regions (Song, 2013). Due to its extensive advantages, P&R has become popular in travel demand management. Based on the literature (Bolger, Colquhoun, & Morrall, 1992), P&R systems have successfully decreased traffic congestion and other external impacts in North America and other regions and countries. P&R systems not only help P&R users reduce their travel costs and increase their traveling comfort, but also serve transportation operators by reducing the demand of parking spaces in city centers (Lam, Holyoak, & Lo, 2001). In addition, P&R systems can lead to a reduction in the level of greenhouse gas emissions as they promote the use of public transportation services for parts of travelers' journeys (Du & Wang, 2014; Lam et al., 2001). In general, P&R systems based on fixed guideway reduce the travel time; however, this benefit is not necessarily limited to fixed guideway systems (Cornejo, Perez, Cheu, & Hernandez, 2014; Hou, Zhao, & Liu, 2020; Niles & Pogodzinski, 2016). Indeed, some of the past research showed rather broad improvements in operations after implementing P&R systems. This is because, theoretically, choice riders are expected to transfer from cars to P&Rs if P&Rs are located optimally (Kimpton, Pojani, Sipe, & Corcoran, 2020). Hence, if a significant number of choice riders opt to use P&Rs instead of cars, the traffic flow on certain routes may improve, which can eventually reduce congestion and travel times of those routes for all travelers.

There is no doubt that a P&R system can be effective and successful if well planned. A significant contributor to a P&R system's success is the suitability of the corresponding public transportation service, including the type and frequency of services, good accessibility, high reliability, and high level of comfort. As such, certain service characteristics of a P&R can play a role in its attractiveness. For instance, a P&R that has access to subways may be more attractive than another that has access to buses only, mainly because of higher regularity and reliability of services. It is important to note that the lack of suitability of the public transportation service at a facility can lead to underutilization after placement (Burns, 1979).

Another important contributor to P&R facilities' success is their distribution and location. If P&R facilities are not conveniently located, potential travelers will opt out of using the facilities, even despite severe traffic congestion and/or high parking cost in the destination. Hence, P&R site selection is extremely important to ensure that all facilities in a system will be effectively utilized by commuters, avoiding oversubscription or underutilization after placement.

Various approaches have been applied for identifying the strategic placement of P&Rs. These approaches include using a set of criteria provided by professional engineers and planners (AASHTO, 2004), demand analysis (Hamid, Mohamad, & Karim, 2007; Hendricks & Outwater, 1998; Hole, 2004) and optimization models (Farhan & Murray, 2008; Song et al., 2017; J. Y. Wang, Yang, & Lindsey, 2004). Over the last few decades, numerous research projects were conducted to investigate how to increase P&R utilization rates and make them successful. The Transit Cooperative Research Program (TCRP) has published several reports that compile best practices of P&Rs, and their planning, management, and implementation strategies (Cherrington, Brooks, Cardenas, Elgart, Galicia, Hansen, Miller, & Walk, 2017; Cherrington, Brooks, Cardenas, Elgart, Galicia, Hansen, Miller, Walk, et al., 2017; Coffel et al., 2012; Turnbull, Pratt, Evans, & Levinson, 2004). Despite their comprehensiveness, these guidelines are mostly generic in nature, prompting cities and transit agencies to develop their own demand estimation models for P&Rs to obtain city-specific plans. To that end, efforts have been undertaken to develop P&R demand models for different cities, considering their demographics, socio-economic, and geographic contexts, as well as their transit infrastructure and networks. Demand models developed by transit agencies such as Texas Transportation Institute (TTI), Tri-County Metropolitan Transportation District of Oregon (TriMet), and Bay Area Rapid Transit (BART) are examples of some of the earlier demand models for P&Rs (Cherrington, Brooks, Cardenas, Elgart, Galicia, Hansen, Miller, Walk, et al., 2017). Therefore, cities that intend to increase their transit ridership through P&Rs may benefit from developing their own P&R demand models to estimate the level of demand for services, given the specific characteristics and preferences of their residents.

Optimization models have also been used as an important approach for finding the best P&R locations under different optimization objectives such as increasing the transit usage, shifting riders from using automobile to public transit, reducing the total travel cost of the network, and bringing the network into a user equilibrium or system optimum state. Linear programming (LP), mixed integer linear programming (MILP), non-linear programming (NLP), p-median, and bi-level programming have been used to formulate strategic placement of P&Rs in the literature.

In this study, a framework is developed that integrates a demand model and a MILP model to optimize the placement of P&R facilities to maximize the total number of commuters who switch from single occupancy vehicles (SOVs) to public transit. These models are specifically presented through a case study for the City of Nashville, a major metropolitan area in Tennessee. The first step in this framework is developing a P&R demand model through a discrete choice model, specifically the multinomial logit model, to understand the mode choice behavior of individuals in a multimodal network. However, this task is complicated by the lack of access to existing survey data that capture the attitude of commuters towards P&R services in the region of interest, a likely issue in many regions. Therefore, to address this issue, an approach is proposed to estimate the P&R demand model using existing data. Next, the framework leverages the estimated proportion of commuters intending to switch to P&Rs from alternatives in a MILP optimization model to find the optimal locations of P&R facilities. Note that such an integrated use of discrete choice and optimization models allows for capturing the proportion of travelers who would use each mode (per their utility in the context of all possible modes) under all feasible solutions. As such, introducing the discrete choice model allows the optimization model to provide more realistic results through capturing the potential behavior of travelers towards using each mode.

Finally, an analysis is performed to examine the potential benefits of replacing the P&R facilities with transit-oriented developments (TODs). TODs are compact, mixed use developments near transit facilities and generally have high-quality walking environments. A comparison of P&R facilities with TODs is performed in the case study, based on the vehicle kilometer traveled reduction (VKT), to provide recommendations about potential placement of TODs in the network.

This report is organized as follows: First, in Chapter 2, a literature review of P&Rs and TODs is conducted. Next, Chapter 3 discusses the existing dataset and its limitation. Chapter 4 describes the methodologies developed. Chapter 5 provides the results of the case study, and finally Chapter 6 concludes the report.

Chapter 2 Literature Review

This chapter provides a literature review of P&Rs and TODs. The review on P&Rs is condensed from a published study, partially supported by this project (Haque, Brakewood, Rezaei, & Khojandi, 2021).

2.1 P&Rs

Due to the extensive literature on P&Rs, inclusion criteria were used to only include the most recent and relevant studies in compiling this report. Specifically, the types of publications considered for this review were peer-reviewed journal articles, conference proceedings, thesis or dissertations, TCRP reports of Transportation Research Board (TRB), publicly available planning documents, and guidelines or toolkits from the state departments of transportation (DOTs). Papers from the United States and those considering hypothetical contexts were included as they provided insights into recent and advanced methods. The following keywords and phrases were searched either in combination or separately: "park-and-ride," "P&R," "TCRP," "planning guideline," "guideline," and "toolkit." Two electronic databases, namely Google Scholar and Transport Research International Documentation (TRID), were used. To focus the review, only studies published from 2011 through July 2020 were included as this period was deemed sufficiently long to observe the recent trends and advancements.

Thirty-seven studies were found. Figure 1 shows the frequency distribution of the publication types of P&R studies in the last ten years. In total, 25 journal articles, seven reports, four conference proceedings, and one thesis were published in the last ten years. Among them, three were TCRP reports, two were transportation institute provided reports, and two were State DOT design guidelines that were available online.

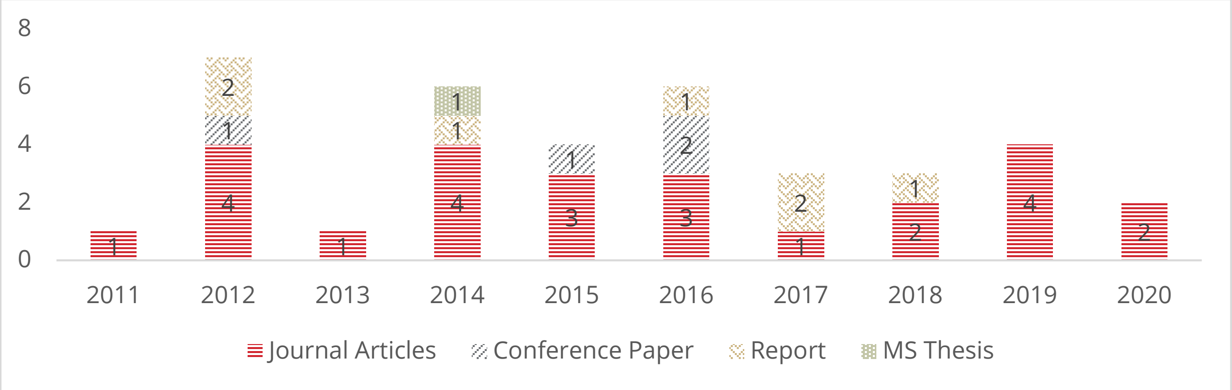

Figure 1. Number of studies included in this review per their year of publication from 2011-2020 (n = 37)

After the data collection process, a text-mining method was applied to identify the themes of P&R research. The authors utilized text-mining methods to classify the existing P&R-based studies. As text-mining helps discover knowledge from unstructured textual data (Feldman & Dagan, 1995), classifying P&R studies based on the words used in the documents is a simple scientific approach rather than doing it manually. In the text-mining process, the available documents were preprocessed to reconstruct the missing data structure. Then dimension reduction techniques were applied to make the text-mining results interpretable (Rajman & Vesely, 2004). QDA Miner

(Péladeau, 2004) and WordStat software ("WordStat 7 User's Guide," 2014) were used for text-mining. In this report, the selected 37 studies were first appended in the QDA Miner. Then, WordStat was used to run the content analysis and prepare a co-occurrences map. Based on the word clusters of the co-occurrences map, six themes of P&R studies were identified. Figure 2 shows the distribution of publications for the six themes, which are described as follows:

1) ***Comparative Studies:*** These studies consisted of comparative analyses between P&R and TODs, between rail-based P&R and bus-based P&R, or between P&R trips and single occupancy vehicle (SOV) trips.
2) ***Guidelines and Best Practices:*** These studies explained the characteristics of successful P&Rs and design recommendations for them. TCRP reports and guidelines by State DOTs on P&Rs fell into this theme.
3) ***Demand Models:*** These studies applied different logit models to identify what factors influenced a rider's mode choice or P&R station choice.
4) ***Network Equilibrium and Optimization:*** These studies used different mathematical programming algorithms and optimization techniques to solve P&R network equilibrium problems.
5) ***Parking Utilization:*** These studies were on parking space utilization of P&Rs.
6) ***Other:*** The remainder of the studies fell into this broad theme that considered all other topics.

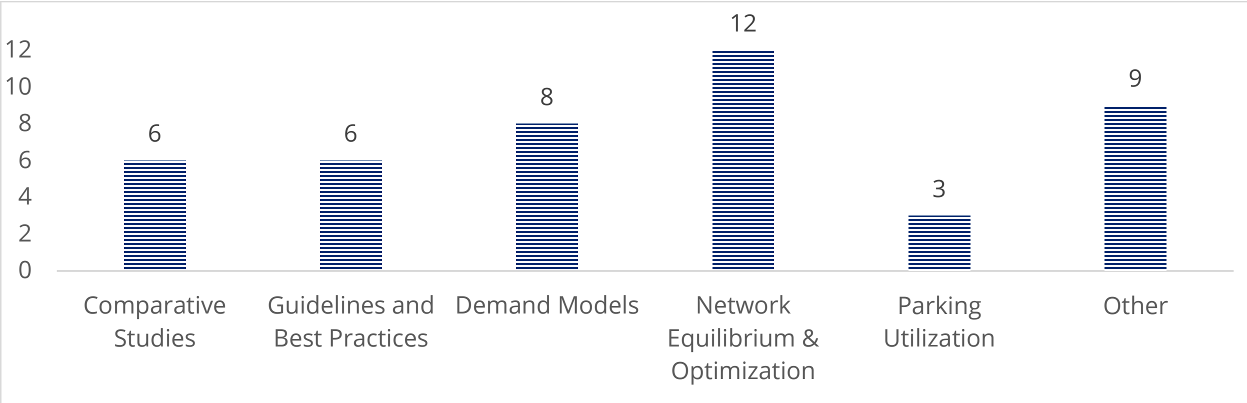

Figure 2. Number of reviewed studies under each theme from 2011-2020 (n = 37; some studies counted multiple times)

2.1.1 Theme 1: Comparative Studies

A summary of key findings for the studies in this theme is provided in Table I. Note that different studies considered different factors. Comparisons based on transit ridership, parking cost, parking structure type, vehicle kilometer traveled (VKT), vehicle hours of delay (VHD), development density, and residential demand calculations (Duncan, 2019; Fan, Jiang, & Erdogan, 2016; Martin & Hurrell, 2012) were seen in P&R and TOD based studies. P&Rs performed better than TODs in locations farthest from downtowns (11-13 km) in terms of VKT reduction. P&R trips were compared to SOV trips, and end-of-line P&Rs resulted in lesser vehicle mileage, fuel consumption, and Green House Gas (GHG) emission. (Truong & Marshall, 2014). Rail-based and bus-based P&Rs were compared in terms of parking space utilization rates (Zhang, 2014) and trip generation rates (Palakurthy, Tung, Cryer, & Bell, 2017). Rail-based P&Rs were observed to have higher utilization rates than bus-based P&Rs. The application of sophisticated statistical models was rare in comparative studies. Only one in six studies used the Tobit model to predict P&R demand and reported that Tobit was a better model to predict bus-based P&R demand (Zhang, 2014).

2.1.2 Theme 2: Guidelines and Best Practices

A summary of key findings for the studies in this theme is provided in Table II. The TCRP reports on P&Rs were TCRP Report 192, Report 153, and Report 69, which summarized the suggested design dimensions and locations of the P&Rs for different area types of US. The distance where P&Rs could be placed from a city center ranged between 10-25 miles, and none of the guidelines suggested to locate P&Rs near the city center. It could be inferred that P&Rs are most likely to succeed in the farthest locations from the city center. Good accessibility from highways, visibility, and security were encouraged to obtain successful P&Rs. TCRP Report 69 discussed the P&R Demand Models prepared by the Federal Transit Administration (FTA), by various transit agencies, and by researchers. The predictors for transit ridership associated with P&Rs were similar in these models. The geographic unit of analysis in most of the models was the half-mile area around the transit stations. The state DOT guidelines were from the Florida Department of Transportation (FDOT) (AECOM, 2012) and the Virginia Department of Transportation (VDOT) (VDOT, 2018). The former provided comprehensive guidelines on P&R lot design and dimensions, and the latter offered distinct guidelines for P&Rs of high density, medium density, and low density areas. However, these existing guidelines and best practice reports did not document some important but contradictory P&R location decisions, which were identified by Mock and Thill (2015). These researchers reported that P&R location preferences may differ between planners and transit agency managers. For locating P&Rs, transit planners in larger cities often prioritized proximity to residential areas and the relationship to the CBD over proximity to highways and congested thoroughfares. Transit agency managers of larger cities often considered P&R demand before land uses, but those of mid-tier cities often placed land use considerations over P&R demand. Transit planners also considered capital costs as a crucial factor in determining which rapid transit stations should have P&Rs.

2.1.3 Theme 3: Demand Models

A summary of key findings for the studies in this theme is provided in Table III. Four studies were on the mode choice model (Cornejo et al., 2014; Fan et al., 2016; Karamychev & van Reeven, 2011; Zhang, 2014), two studies were on station choice models (Pang & Khani, 2018; Webb & Khani, 2020b), and one study was on preferred choice of scenarios (Cao & Duncan, 2019). Number of boardings was predicted by one study (Niles & Pogodzinski, 2016). In the mode choice models, demography, land use, road density information, VKT, and VHD were used for predicting P&Rs as mode choice. In the station choice models, travel time and trip-related information were used to predict P&R station choices by commuters. All the studies used discrete choice models as their methods, such as binary logit (Cornejo et al., 2014), mixed logit (Pang & Khani, 2018), MNL (Cao & Duncan, 2019; Fan et al., 2016; Karamychev & van Reeven, 2011; Zhang, 2014), nested logit (NL) (Webb & Khani, 2020b), Ordinary Least Square (OLS) and Poisson regression models (Niles & Pogodzinski, 2016).

2.1.4 Theme 4: Network Equilibrium and Optimization

A summary of key findings for the studies in this theme is provided in Table IV. The studies reported that optimally located P&Rs had the ability to influence riders to shift from automobiles to public transit. However, their optimal location, number, size, and optimal parking fee depended on the objective functions and constraints considered in these P&R network design problems or models. The types and numbers of objective functions and constraints differed based on the goals of these studies. Some common objective functions in these studies were minimization of total travel cost, total travel time, VKT, VHD, budget, and parking construction costs, as well as maximization of P&R users. In some cases, more than one objective was considered, and a bi-objective programming (BP) model was used to deal with conflicting objectives. Constraints varied across studies, but parking space or P&R capacity constraints were common in some studies. Other types of constraints considered were equilibrium constraints (EC), complimentary constraints (CC), demand and flow conservation, equity constraints, and reliability constraints.

The network equilibrium approach to achieve optimal P&R locations typically had two levels in their analysis: a) logit models for modal split and b) different user equilibrium (UE) models for route choice in the network. Some studies considered P&Rs as an independent mode and used MNL as their logit model and UE models for the route choice (Fan et al., 2016; H. Wang, Meng, & Zhang, 2015). In contrast, some studies considered P&Rs to have qualities of both cars and transit, and these studies used more sophisticated logit models such as Cross Nested Logit Model (CNL) (Chen, Liu, Hua, & Kim, 2017) and Nested Logit (NL) (Hou et al., 2020). Additional models like Combined Modal Split and Traffic Assignment (CMSTA) (Chen & Kim, 2018; Hou et al., 2020; Liu, Chen, Meng, & Kim, 2018), Mathematical Program with Complementary Constraints (MPCC) (Song et al., 2017), Mathematical Programming Model with Equilibrium Constraints (MPEC) (Liu et al., 2018), and Nonlinear Complementary Problem (NCP) (Islam, Liu, & Sarvi, 2015) used various algorithms to solve the optimization problem, including Genetic Algorithm (GA) (Hou et al., 2020; Islam et al., 2015), Active Set Algorithm (ASA) (Song et al., 2017), Variational Inequality (VI) (Chen et al., 2017), and Self-Adaptive Gradient Projection (SAGP) (Chen & Kim, 2018). Besides these linear and non-linear mathematical programs, there were some other approaches to find optimal P&R locations such as the p-hub and the Break Even Distance (BED) approaches. The former was a mixed linear program formulation that considered P&Rs as hubs (Aros-Vera, Marianov, & Mitchell, 2013), and the latter was used to define catchment areas of P&Rs (Holguın, Yushimito, Aros-Vera, & Reilly, 2012).

2.1.5 Theme 5: Parking Utilization

A summary of key findings for the studies in this theme is provided in Table V. The studies reported that parking space utilization is impacted by parking fees. Lower or no parking fees were more desirable than higher parking fees by P&R users. P&R users were willing to walk 10-15 minutes for an ensured parking spot and pay fees higher than general parking fees of P&Rs. Parking utilization was found to be lower for a higher percentage of the driving population near P&R lots by one study (Zhao, Chen, Jiao, Chen, & Bischak, 2019). P&Rs were mostly used by SOVs and less by other modes by other two studies (Gayah, Stieffenhofer, & Shankar, 2014; Stieffenhofer, Barton, & Gayah V, 2016).

2.1.6 Theme 6: Other

A summary of key findings for the studies in this theme is provided in Table VI. Three studies found a positive impact of P&Rs on traffic, social welfare (Karamychev & van Reeven, 2011), VKT (Duncan & Cook, 2014), and transit operations (Niles & Pogodzinski, 2016). However, conflicting evidence was found in Charlotte, where replacing P&Rs with moderately dense housing reduced VKT in five out of seven LYNX stations (Duncan & Cook, 2014). P&Rs were also evaluated based on economic analysis, transit professionals' priorities, job accessibility, travel time, and safety in some studies. Discrete choice models were used for the investigation by four studies, but five studies used different methods.

Table I Summary of the studies in the "Comparative Studies" theme

Author, Year	Location	Data Collection	Mode	Method	Key Findings
(Martin & Hurrell, 2012)	Bay Area, California	User Survey, Sample = 11 suburban stations of BART	Rail	Transit ridership and cost of station parking calculation	(i) Surface parking was a better option than high rise TOD. (ii) Surface parking was better than structured parking if the land value was less than $2mi/acre.
(Truong & Marshall, 2014)	Denver, Colorado	Onboard survey on regional transportation district (RTD) riders. Sample = 2019	Rail	Vehicle mileage calculation, fuel consumption, the ratio of CO2 emission calculation	(i) P&Rs located in inner corridors were less effective than end-of-line P&R stations in reducing GHG emissions. (ii) Inner corridor P&Rs caused additional driving trips and SOV transit access car trips.
(Zhang, 2014)	Delaware	Train Demand Survey, 2010; Bus Demand Survey, 2013	Rail and Bus	Gravity and mode choice model for rail-based P&R, Tobit model for Bus-based P&R	(i) Rail-based P&Rs generally have one destination and Bus-based P&Rs have multiple destinations. (ii) Rail-based P&Rs have higher utilization rates than bus-based P&Rs in Delaware.
(Fan et al., 2016)	Hypothetical	Dataset is adopted from Burgess (2008) paper (Burgess, 2008)	Rail	Residential relocation model and Travel Demand Model	(i) Choose the option that increases ridership and decreases VKT and VHD. (ii) With increasing parking space, P&R is more effective in increasing ridership and decreasing VKT/VHD than a TOD of a same land use area.
(Palakurthy et al., 2017)	Denver, Colorado	Trip Generation Data 2015. Sample = 40 P&Rs of RTD	Rail and Bus	P&R vehicle accumulation calculation, weighted average peak hour, and	(i) Regional bus P&Rs can use both regression equations and weighted average rates for trip generation estimates.

Author, Year	Location	Data Collection	Mode	Method	Key Findings
				daily trip generation rates/occupied space	(ii) Daily trip generation rate/occupied space for bus and rail as per ITE was 9.62 and 3.91, but as per RTD was 3.5 and 3.91, respectively.
(Duncan, 2019)	Charlotte, North Carolina	2009 onboard CATS passenger survey (Sample=351); 2008 on-board LYNX passenger survey (Sample = 721); 2011 daily LYNX boardings (7 stations); Mecklenburg County Property Database	Rail	VKT calculations	(i) Farthest located (11 – 13 km) P&R resulted in more VKT reduction than TOD.

Table II Summary of the studies in the "Guidelines and Best Practices" theme

Author, Year	Document	Location	Method	Key Findings
(Coffel et al., 2012)	TCRP Report	US	Stakeholder Interviews, Literature Review, Case Study	(i) P&Rs can be 10-15 miles away from the city center for the case of inner suburbs, 15-25 miles away for the case of outer suburbs, and over 25 miles away for the case of exurbia. (ii) Maximum size of lot (typical) = 900-1200 spaces. (iii) Parking space per acre = 125-135. (iv) Maximum passenger accumulation/shelter = 80-150 people. (v) Desirable pedestrian walking distance = 1,200 feet (max), 5' walkway width (min).
(Cherrington, Brooks, Cardenas, Elgart, Galicia, Hansen, Miller, & Walk, 2017)	TCRP Report	US	Literature Review, Industry Scan, Case Study	(i) P&Rs should be located along good highways with transit access and visibility, strong ridership potential, and a perception of security. (ii) Incorporating community input also helps in successful P&Rs.
(Cherrington, Brooks, Cardenas, Elgart, Galicia, Hansen, Miller, Walk, et al., 2017)	TCRP Report	US	Literature Review, Industry Scan, Case Study	(i) Transit agency-specific Demand Models are: 1. Milwaukee (Portland, Oregon) P&R estimates developed by TriMet (2011). 2. Regional peer site model for Fort Bend County (Texas) Public Transportation developed by TTI (2012). 3. Access policy methodology developed by BART (2005).
(AECOM, 2012)	State DOT Guidelines	Florida	NA	(i) Properties of P&Rs are external features, internal lots, and transit services. (ii) The priority of closeness to transfer terminal: (1) bicycle parking, (2) accessible parking, (3) kiss-and-ride and other drop-offs/pickup areas, (4) short-term parking, (5) long term parking.

Author, Year	Document	Location	Method	Key Findings
				(iii) Automobile parking layout: 9′ x 18.5′, 90-degree standard or 8′ x 16′, 90-degree compact dimensions. Both right angle and angled parking are allowed. (iv) Signage and marking should be Manual on Uniform Traffic Control Devices (MUTCD) compliant.
(VDOT, 2018)	State DOT Guidelines	Virginia	NA	(i) Specification of P&Rs in high-density areas: Reside in multimodal suburban or urban areas. 90° parking. 8′X20′ kiss-and-ride areas. 50′ or 70′ long bus boarding areas. 1 bicycle parking for every 10-20 vehicle spaces with 2 point locking capability. LED lights. (ii) Specification of P&Rs in medium density areas: Reside near interchanges or suburban areas. Parking requirements similar to high-density areas. No kiss-and-ride area. Bike parking with a minimum of 2-3 racks. LED lighting. (iii) Specification of P&Rs in rural areas: Reside near interstates or arterial roadways. 45° or 60° angle parking. 50′ to 70′ long bus boarding areas. 15′ parking aisles for lots with one-way traffic and 60° parking.
(Mock & Thill, 2015)	Journal Article	US	Interviews and surveys of 145 transit professionals	(i) Transit planners consider capital cost as a crucial factor in determining which rapid transit station should have P&Rs. (ii) Transit agency managers of large cities prefer P&R demand over land use, in contrast to planners and engineers, but those of mid-tier cities prefer land use over P&R demand. (iii) For locating P&Rs in larger cities, transit planners prioritize proximity to residential area and relationship to primary activity center or CBD over proximity to highways or congested thoroughfare, but the priorities swap in mid-tier cities.

Table III Summary of the studies in the "Demand Models" theme

Author, Year	Location	Data Collection	Mode	Model	Dependent Variable	Key Findings
(Karamychev & van Reeven, 2011)	Hypothetical	NA	Rail and Bus	MNL	Choice set of modes (Auto, Transit, and P&R)	(i) Remote P&Rs can reduce traffic if more riders prefer to choose cars. (ii) Remote P&Rs are attractive for both car and transit users when congestion and parking at the city center is considered.
(Cornejo et al., 2014)	El Paso, Texas, USA	Survey, 447 El Paso residents	Bus	Binary Logit	Choice set of modes (P&R or other modes)	(i) P&R utilization rates are positively associated with: road density, employment density and percentages of people between 18-34 and 65+.
(Zhang, 2014)	Delaware, USA	Train Demand Survey, 2010; Bus Demand Survey, 2013.	Rail and Bus	MNL, Tobit	Choice set of modes (P&R or Auto)	(i) Tobit is a better model for predicting bus-based P&R demand than MNL model. (ii) MNL model can be combined with gravity model to estimate rail-based P&R demand.
(Fan et al., 2016)	Hypothetical	Dataset is adopted from Burgess (2008) paper (Burgess, 2008)	Rail	Four step travel demand model with residential relocation model	Choice set of modes (Auto, metro, and P&R)	(i) Travel demand changes significantly (ridership increases and VKT/VHD reduces significantly) when a new P&R or TOD is developed. (ii) Travel demand reduces when existing P&R is replaced with a limited scale TOD.

Author, Year	Location	Data Collection	Mode	Model	Dependent Variable	Key Findings
(Niles & Pogodzinski, 2016)	The western US	American Community Survey, 2010; Transit agencies	Bus	OLS and Poisson Regression	Boarding, Boardings per trip	(i) Transit ridership can be influenced more by P&Rs than residential housing.
(Pang & Khani, 2018)	Austin, Texas, USA	Onboard survey by CapMetro, 418 riders	Rail and Bus	Logit, Logit with interaction terms, Mixed Logit, Mixed Logit with correlation	Choice set of P&Rs	(i) Travelers prefer shorter auto travel time from the origin to the P&R, transit in-vehicle-time greater than 10 minutes, and fewer transfers during transit trips.
(Cao & Duncan, 2019)	Twin Cities, Minnesota	Online Survey, 570 riders	Rail	MNL	Is the scenario a preferred choice? (Yes/No)	(i) Influence of walking distance is stronger than intersection safety, pedestrian infrastructure, and building appearance on P&R users' choices.
(Webb & Khani, 2020b)	Twin Cities, Minnesota, USA	Onboard survey by Metro Transit, 1690 users	Rail and Bus	MNL, Nested Logit, Mixed Logit	Choice set of P&Rs	(i) Riders preferred those P&Rs that had a small distance ratio. (ii) Distance ratio indicates how "out of the way" P&R is when direction from origin to destination is considered.

Table IV Summary of the studies in the "Network Equilibrium and Optimization" theme

Author, Year	Location	Mode	Method	Key Findings
(H. Wang, Meng, & Zhang, 2014)	Hypothetical	Rail	DUE	(i) P&R parking fee scheme can be used to improve the network travel efficiency with the second-best road pricing.
(H. Wang et al., 2015)	Hypothetical	Rail	UE	(i) Total travel cost decreased with an increasing number of parking spots at destination.
(Holguın et al., 2012)	Manhattan New York	Rail	BED	(i) Location of P&R depends on Transit LOS. (ii) P&R catchment area had a parabolic shape. (iii) Better transit LOS provides larger catchment areas.
(Aros-Vera et al., 2013)	Queens, New York	Rail	P-Hub	(i) Five best locations were identified from 21 candidate P&Rs. (ii) Demand derived by the P-hub approach was lower than that of Holguin-veras et al. (2012) model.
(Lu & Guo, 2015)	Anaheim, California	Rail & Bus	BP	(i) Passenger Flow Volume per Cost (PFVC) is regarded as an index for the level of the rate of investment return.
(Islam et al., 2015)	Hypothetical	Rail	NCP, GA	(i) The value of network reliability in the worst P&R scenario was higher than the no P&R scenario.
(Fan et al., 2016)	Hypothetical	Rail	UE	(i) TOD density beyond the equilibrium point can cause higher investment costs and attract less residents.
(Song et al., 2017)	Hypothetical	Rail	MPCC, ASA	(i) Optimal design reduces the social cost by 32.59% from status quo condition. (ii) It also encourages riders to shift from automobile to transit and P&Rs.
(Chen et al., 2017)	Hypothetical	Rail	CNL, UE, VI	(i) CNL and UE model with mean-excess stochastic travel times influenced the mode choice and route choice pattern.
(Chen & Kim, 2018)	Hypothetical	Rail	EC-CMSTA, SAGP	(i) By lowering the environmental protection threshold, auto usage can be reduced, and more travelers will shift to transit.
(Liu et al., 2018)	Hypothetical	Rail	MPEC	(i) The Remote P&R scheme effectively mitigates congestion.

				(ii) Multimodal expected total travel time (METTT) improves with budget increase until budget reaches a suitable level.
(Hou et al., 2020)	Hypothetical	Rail & Bus	CMSTA (NL-UE), GA	(i) Optimally located Remote P&Rs influence network users to use public transit. (ii) Optimally located P&Rs also improve social benefits.

Table V Summary of the studies in the "Parking Utilization" theme

Author, Year	Location	Data Collection	Mode	Method	Key Findings
(Gayah et al., 2014)	Central Puget Sound Region, Seattle, Washington	On-site audit (10 P&R lots), intercept and electronic survey (17 P&R Lots), sample = 3341	Rail and Bus	Calculate person occupancy of parked vehicles, analysis of users' opinions	(i) Person occupancy of parked vehicles for all P&Rs was about 1, meaning the majority of P&R users arrive by SOVs. (ii) P&R users are willing to pay $1.5 as a general parking fee, $1.83 for an ensured parking spot, and $1.53 on average for an ensured space that is 10-15 minutes walking distance away from the P&R. (iii) 100% of parking space at 7 out of 10 P&Rs were filled before 9 am.
(Stieffenhofer et al., 2016)	Central Puget Sound Region, Seattle, Washington	On-site audit (9 P&R lots), intercept and electronic survey (17 P&R Lots), sample = 3341	Rail and Bus	Person efficiency, analysis of users' opinions	(i) Person efficiency is a more straight- forward method compared to person occupancy of parked vehicles. (ii) Person efficiency values for all P&Rs were about 1.
(Zhao et al., 2019)	King County, Washington	Data from 2004 - 2017. Source: King County Metro Transit, King County GIS Open Data, Puget Sound Regional Council, American Community Survey, US Energy Information Administration	Bus	Tobit Model	(i) There is a positive association between the utilization rate of P&Rs and transit ridership, road density, employment density, mixed land uses, percentages of people aged between 18 and 34 and people over 65, the percentage of Caucasians, and the percentage of low-income people. (ii) Transit ridership within a 0.25-mile buffer is positively associated with the utilization rate of P&R lots.

Table VI Summary of the studies in the "Other" theme

Author, Year	Location	Mode	Method	Key Findings
(Karamychev & van Reeven, 2011)	Hypothetical	Rail and Bus	MNL	(i) P&Rs can reduce traffic if more riders prefer to choose cars. (ii) P&Rs can increase social welfare if traffic moves toward the periphery.
(Li, Zhou, Zhang, & Zhang, 2010)	South Bay, CA	Bus	Time-dependent shortest path and K shortest path algorithm	(i) Preliminary case studies resulted in satisfactory performance by the trip planning system.
(Holguín-Veras, Reilly, Aros-Vera, Yushimito, & Isa, 2012)	New York	Rail	Economic analysis	(i) Present value of benefits of each of the top 20 candidates were >$44 million. (ii) Top five P&Rs had a weighted average savings of $12/user/day.
(Duncan & Christensen, 2013)	USA	Rail	Binary Logit Model (Will the LRT station have P&R? Yes=1, No=0)	(i) P&Rs of LRT stations are more likely to be found in less urban places where land is cheaper and density is lower, and in politicized municipal environments.
(Duncan & Cook, 2014)	Charlotte, NC	Rail	VKT calculation	(i) P&Rs replaced by moderately dense housing having 50-100 units/hectare reduced VKT for five out of seven LYNX stations.
(Mock & Thill, 2015)	USA	Rail and Bus	Ranking P&Rs placement factors with a 4-point Likert scale	(i) To place P&Rs in mid-tier cities, transit planners prioritized convenience over economics, but the priorities swap in larger cities.
(Niles & Pogodzinski, 2016)	The western US	Bus	OLS and Poisson Regression; Route-level & Stop-level analysis	(i) Productivity of bus operations can increase by expanding parking in suburban P&Rs.

(Carlson & Owen, 2019)	Twin Cities, Minnesota	Rail	Calculation of Worker-Weighted Average Job Accessibility	(i) A 30-minute P&R trip measure increases average worker-weighted job accessibility by 230% compared to a walk-to-transit measure.
(Cao & Duncan, 2019)	Twin Cities, Minnesota	Rail	MNL	(i) P&R users are more likely to walk an additional 1.8 blocks from P&R to the stop if they are provided with better intersections and a welcoming walking environment.

2.2 TODs

2.2.1 Best Practices of TOD

A literature review was conducted to find the best practices of TOD. The most relevant literature was drawn from three TCRP reports (Arrington & Cervero, 2008; Cervero et al., 2004; Evans, Pratt, Stryker, & Kuzmyak, 2007). These reports summarized the lessons learned from the experience, challenges, and prospect of TOD in the U.S., contained travelers' responses to TOD systems, and the effects of TOD on housing, parking, and travel. Key findings from these reports are summarized in Table VII.

Table VII Key Findings related to TOD based on three TCRP reports, namely reports 102, 95, and 128

Author, Year	Title	Method	Key Findings
(Cervero et al., 2004)	TCRP 102 TOD in the United States: Experience, Challenges, and Prospects	Literature Review, Comprehensive Survey, Interviews, Case Study	Benefits of TOD: curbing sprawl, reducing traffic Overlay zones can be used for TOD site designs Political barriers to TOD is NIMBY
(Evans et al., 2007)	TCRP 95 Chapter 17 Traveler Response to Transportation System Changes Handbook	Traveler Response Survey; Case Study	Classifies TOD based on/as: Regional Context (suburban, city) Land Use Mix (different mix of office, retail & residential) Primary Transit Mode (LRT, Metro, BRT, commuter rail) Indicators of successful TOD: Essential & Supportive
(Arrington & Cervero, 2008)	TCRP 128 Effects of TOD on Housing, Parking, and Travel	Literature Review, Assessment of TOD housing transportation performance	Factors that most influence transit ridership are station proximity, transit quality, & parking policies.

2.2.2 Legislation, Planning, and Policy Documents

A review was conducted on legislation, planning, and policy documents regarding TODs. A summary of the review and key findings regarding Nashville and two Nashville's peer cities, namely, Atlanta and Charlotte, are included in Table VIII.

Table VIII Key Findings from TOD legislation, planning, and policy documents

Year	Document	Location	Key Points
2010	MARTA Transit Oriented Development Guidelines (MARTA, 2010)	Atlanta	Pedestrian access from surrounding development will receive the highest planning priority, followed by bicycle and feeder transit. Automobile access, whether drop-off or park-and-ride, will receive a lower planning priority. Limited parking capacity, shared parking Joint development on existing Park-and-Ride lots based on ridership & utilization of Park-and-Ride Park-and-ride replacement will be decided on a case-by-case basis, with no assumption that replacement will uniformly be 1:1.
2018	Donelson Transit Oriented Redevelopment Plan (Nashville and Davidson County Tennessee, 2018)	Davidson County, Nashville	To provide a mix of uses and a high-quality pedestrian environment around a defined center To minimize the total number of parking spaces needed in the redevelopment district Conditional Uses Parking Structure (freestanding) Standalone surface parking lots

2019	City of Charlotte Chapter 15. Transit Oriented Development Districts (City of Charlotte, 2019)	Charlotte	Four types of TODD: TOD-UC Transit Urban Center TOD-NC Transit Neighborhood Center TOD-CC Transit Community Center TOD-TR Transit Transition Public Transit Facility Facilities operated by (Charlotte Area Transit System) CATS as part of the public transit system, which includes transit stations and park-and-ride lots. Public Transit Facility is permitted in all the types of TODD

Chapter 3 Data

The output from the Daysim Activity-based demand model for the City of Nashville is used. These data are provided by the Metropolitan Planning Organization (MPO). Specifically, the “trip” dataset, “person” dataset, and “household” dataset are used, which predict the household and person travel choices at a microzone-level on a minute-by-minute basis. These datasets include trip information of individuals in Maury, Williamson, Rutherford, Wilson, Sumner, Robertson and Davidson, which is partitioned into three regions: “Far” areas (Far North, Far NE, East, Far SE, Far West, and Far South), “Near” areas (Near North, Near NE, Near SE, Near West, Near South, and Near SW), and the CBD area.

A total of 23,864 morning rush hour trips with the destination of the Nashville CBD are included in the “trip” dataset. Note that these data only include “travel time” as an alternative specific attribute. Four types of alternative modes are observed in the dataset, namely, single occupancy vehicle (SOV), high occupancy vehicle with two individuals (HOV2), high occupancy vehicle with three individuals (HOV3), and transit. Note that without loss of generalizability, HOV2 and HOV3 modes are concatenated together and denoted as HOV in the remainder of the report to facilitate the analysis. There is information about 60,995 households in the “household” dataset and attributes of 117,552 individuals in the “person” dataset. Several socio-economic and demographic variables such as gender, age, income, household size (the number of individuals in the house), household workers (the number of workers in the house), and household vehicles (the number of vehicles in the house) are included in the “household” and “person” datasets. Table IX presents a descriptive analysis of the variables used in this report.

The trip dataset presents two main limitations. First, as seen in Table IX, the distribution data across the travel modes in this dataset is imbalanced. For instance, travel by SOV is very prominent, while travel by public transport happens rarely. Chapter 4 discusses the problems that these imbalanced data cause when using discrete choice models and describes an approach to balance the data before applying the discrete choice models to improve model performance. Second, clearly, there is no information about the P&R mode in the dataset. In order to reach the objective of this report, which is improvement of P&R services, predicting the behavior of commuters with respect to P&R mode is necessary. This prediction can be obtained by implementing a demand model on the appropriate data (e.g., survey data) that includes the modes under investigation (i.e., P&R mode in this case). Hence, due to the paucity of such data, discrete choice models are built on the current data for the available modes and then an approach is provided in Chapter 4 to estimate the behavior of P&R users. It is important to note that before the proposed framework can be implemented in practice, appropriate data must be collected, possibly through surveys, and used in the framework to obtain actionable results.

Table IX Descriptive analysis of the variables considered

Variable description	Category	%	Variable description	Min	Max	Mean	SD
Mode Choice	SOV	59					
	HOV2 + HOV3	34[†]					
	Transit	7					

Categorical Variables		
Person Gender	Male	50.4
	Female	49.6
Person Type	Full time worker	67.16
	Part time worker	5.87
	Non-working adult age 65+	3.61
	Non-working adult age <65	8.79
	University student	2.69
	High school student age 16+	3.47
	Child age 5-15	2.79
	Child age 0-4	5.62
Person Worker Type	Not a paid worker	24.41
	A paid full-time worker	67.16
	A paid part-time worker	8.43
Person Student Type	Not a student	85.47
	Full-time student	14.53
Paid parking at workplace	No	63.47
	Yes	36.53
HH Own or Rent	Owned	58.56
	Rented	38.72
	Other	2.72
HH Residence Type	Detached single house	66.34
	Duplex/triplex/rowhouse	4.89
	Apartment/condo	25.89
	Dorm room/rented room	1.55
	Other	1.33
Origin Purpose	None/home	50.31
	Work	6.29
	School	0.18
	Escort	14.38
	Medical	12.36
	Shop	4.68
	Meal	1.73
	Social	2.35
	Change mode inserted purpose	7.72

Continuous Variables				
TT-SOV (min)	6.98	131.48	45.34	24.99
TT-HOV (min)	6.50	86.79	30.18	12.89
TT-Transit (min)	12.88	145.53	62.99	21.14
Person Age (years)	0	93	37.81	17.54
HH Size	1	11	3.09	1.81
HH Vehicles	0	4	2.01	1.01
HH Workers	0	7	1.55	0.88
HH Full Time Workers	0	7	1.33	0.87
HH Part Time Workers	0	4	0.15	0.40
HH College Students	0	4	0.10	0.35
HH Kids Age 5-15	0	6	0.50	0.91
HH Kids Age 0-4	0	4	0.30	0.65
HH Income ($)	2015	775516	81861	80692

Destination Purpose	None/home	0.65
	Work	58.42
	School	4.30
	Escort	9.07
	Medical	12.73
	Shop	5.14
	Meal	3.62
	Social	6.07

†HOV2 and HOV3 modes are merged in the dataset

Note: HH = Household, TT = Travel Time

Chapter 4 Methodology

This chapter first presents logit models, which is condensed from a study, partially supported by this project (Rezaei et al., 2021). Next, it proposes two approaches for predicting the behavior of commuters with respect to the P&R mode, which is complicated by the paucity of data regarding the P&R mode in this study. Finally, the optimization model is provided.

4.1 Logit Models

In this section, first, three important discrete mode choice models typically used in the travel demand modeling are briefly described. Then, the problem caused by imbalanced data in the prediction capability of logit models is explained and an imbalanced learning approach for eliminating this problem is described. Finally, the evaluation metrics used to evaluate the performance of logit models are introduced.

4.1.1 Logit Model Description

4.1.1.1 Multinomial Logit Model

The multinomial logit (MNL) model is developed based on the utility maximization rule implying that a decision-maker will choose an alternative from a set of available alternatives that maximizes their utility (Koppelman & Bhat, 2006). In the base MNL model, the expected utility comprises the observed and unobserved components:

$$U_{ik} = \beta x_{ik} + \varepsilon_{ik}, \tag{1}$$

where, U_{ik} is the expected utility perceived by individual i for alternative k (out of a total of K alternatives), x_{ik} is a vector of observed features related to alternative k and/or individual i, and β is a vector of coefficients to be estimated. The unobserved part of the expected utility is captured by the random error ε_{ik}. Different logit models have been developed by considering different assumptions for the coefficients and error terms. In the MNL model, it is assumed that the random error term has the Gumbel distribution and coefficients are fixed for all individuals (M. E. Ben-Akiva, Steven R. Lerman, and Steven R. Lerman, 1985). Hence, the choice probability for this model is defined as:

$$p_{ik} = \frac{e^{\beta x_{ik}}}{\sum_m e^{\beta x_{im}}}, \tag{2}$$

where p_{ik} is the probability that individual i chooses alternative k. Basic assumptions in the MNL model results in the IIA property (proportional substitution patterns across alternatives).

4.1.1.2 Nested Logit Model

The nested logit model has been derived to modify the MNL model to solve its IIA limitation, while holding most of the computational advantages of the MNL model (M. E. Ben-Akiva, 1973; Börsch-Supan, 1987). In the nested logit model, those alternatives that are similar to each other can be grouped into disjoint subsets and the correlation between alternatives within a nest is allowed, while a zero correlation amongst nests is maintained. Suppose that alternatives are partitioned into S disjoint subsets $B_1,\ldots,B_S$. Then, the utility of individual i for alternative k can be described as follows:

$$U_{ik} = V_{ik} + W_{i,s_k} + \varepsilon_{ik}, \tag{3}$$

where V_{ik} is the component of the utility describing alternatives, W_{i,s_k} denote the characteristics of the nest s_k, s_k, and ε_{ik} follow a generalized extreme value (GEV). The probability of choosing alternative k in nest s_k can be defines as:

$$p_{ik} = p_{ik|s_k}\, p_{i,s_k}, \tag{4}$$

where

$$p_{i,s} = \frac{e^{W_{is} + \lambda_s Q_{is}}}{\sum_{l=1}^{S} e^{W_{il} + \lambda_l Q_{il}}} \tag{5}$$

$$p_{ik|s_k} = \frac{e^{\frac{V_{ik}}{\lambda_{s_k}}}}{\sum_{m \in s_k} e^{\frac{V_{im}}{\lambda_{s_k}}}} \tag{6}$$

$$Q_{is} = \ln \sum_{k \in B_s} e^{\frac{V_{ik}}{\lambda_s}} \tag{7}$$

The nest parameter λ_s determines the degree of freedom in the unobserved utility between alternatives in nest s, and it ranges between 0 and 1. When $\lambda_s = 1$, there is no correlation between alternatives within nests and the model returns to the MNL model. On the other hand, small λ_s indicates that correlation between alternatives in nests exists (Webb & Khani, 2020a).

4.1.1.3 Mixed Logit Model

The mixed logit model provides more flexibility, compared with previously discussed logit models. The model allows for individual-specific coefficients, correlation in the unobserved factors, and unrestricted substitution patterns. The utility function is obtained as

$$U_{ik} = \beta_i x_{ik} + \varepsilon_{ik}, \tag{8}$$

where β_i is the coefficient vector with length L (the number of features in the model).

Because estimating the parameters for each individual requires a large number of choice observations per individual, β_is are often considered as random draws from a distribution whose parameters are estimated. Therefore, the conditional choice probability of selecting the alternative k for individual i is given by random draw β_i and is as follows:

$$p_{ik}|\beta_i = \frac{e^{\beta_i X_{ik}}}{\sum_m e^{\beta_i X_{im}}}. \tag{9}$$

Assuming that the coefficient vector $\boldsymbol{\beta_i}$ is one-dimensional, the unconditional probability can be obtained as

$$p_{ik} = E(p_{ik}|\beta_i) = \int_{\beta} (p_{ik}|\beta) f(\beta) d\beta \,, \tag{10}$$

Where $f(\beta)$ is the probability density function of β. When the coefficient vector β_i is a vector of length L, this probability cannot be estimated by the quadratic methods. Therefore, the simulated maximum likelihood is used for parameter estimation (Cheng et al., 2020; Train, 2003).

4.1.2 Problem Caused by Imbalanced Data

Mode choice models are often used for behavioral and predictive analysis. Behavioral analysis involves using the model to explain observed data. Predictive analysis involves using the model to make future predictions. The capabilities of the model in behavioral and predictive analysis may be impacted by the data used in model fitting. This is specifically the case where the data are imbalanced, which is an issue that is generally present in travel demand data. In travel demand data collected in most cities in the US, the transit mode is generally less represented, compared with modes such as SOVs. This is indeed the case in the dataset used in this study. As a result, the mode choice model fitted to the data may erroneously learn to undervalue the less represented classes, causing it to present a higher prediction error for such classes (King & Zeng, 2003; F. Wang & Ross, 2018). In this case study, it is particularly important for the model to be accurate with respect to the less represented transit mode. Therefore, the issue at hand is addressed by leveraging balancing techniques prior to model training.

4.1.3 Imbalanced Learning Technique

Various techniques have been developed to address imbalanced data (Haixiang et al., 2017; Kotsiantis, Kanellopoulos, & Pintelas, 2006). These techniques are classified in three categories: data preprocessing approach, algorithmic approach, and feature selection approach (Kotsiantis et al., 2006).

To address class imbalance in this report, the data preprocessing approach was used. In general, data preprocessing helps with balancing the class distribution in the data. The specific techniques include over-sampling the less represented class, under-sampling the more represented class, or a hybrid approach where a combination of over- and under-sampling is used (Haixiang et al., 2017; Kotsiantis et al., 2006). Particularly, in this report, the following hybrid approach was used. At first, let n denote the average number of existing observations per mode, calculated by dividing the total number of observations by the number of modes. Then, if the observations of a given mode were less than the average n, the observations were sampled randomly with replacement from the dataset for this mode until the total number of observations in the mode reached n. On the other hand, if the observations of a given mode were more than the average n, the extra observations in the mode were randomly removed from the dataset. After these steps, exactly n observations remained in each travel mode. Note that this procedure did not change the total size of the dataset.

4.2 P&R Demand Estimation Approach

In order to estimate demand for P&R facilities, coefficients of variables in the utility function of P&Rs in logit models were required. Note that these coefficients are usually obtained from calibrating logit models based on the survey data; however, as discussed earlier, these data were not available for the City of Nashville and its surrounding areas. Therefore, two alternative approaches were devised to estimate coefficients of the individual and alternative specific attributes in the utility function of P&R users in logit models.

4.2.1 Approach 1

One approach was to use the output coefficients from past published works. There were only a limited number of relevant case studies in the US, Canada, and Australia that analyzed P&R users by discrete choice models. Unfortunately, most of these studies were not usable in this study, mainly because they considered attributes such as travel cost, transit waiting time, ratio of total travel distance to access to station, among others, that were not available in the dataset (Habib, Mahmoud, & Coleman, 2013; Pang & Khani, 2018; Sargious & Janarthanan, 1983; Sharma, Hickman, & Nassir, 2019). The paper that was most relevant to this work was Cornejo et al., 2014; however, even this work posed a major limitation. Table X presents the output coefficient of this paper. As seen in the table, travel time is categorized based on time ranging between 0-35 minutes, which is on the lower end of the travel times seen in the available dataset, ranging between 6-130 minutes. Therefore, to be able to use this published study, it was needed to make various assumptions and/or adjust the ranges of the travel time categories. To do so, the normalizing method was used to change travel time values in the dataset and make them comparable to the values in this work.

Table X MNL model outputs in (Cornejo et al., 2014)

Variables	Coefficient	t-statistics	p-value	Marginal Effects
Constant	0.8606	1.763	0.0782	0.1886
Age and Household Income (1 if 1 – 24 or younger & less than $24,999 / year, 0 otherwise)	0.5896	2.105	0.0353	0.1231
Household Size (1 if 2 persons, 0 otherwise)	–0.4472	–1.354	0.1759	–0.1024
Car Ownership (0 if 0 cars, 1 if 1 car, …, 5 if 5 cars or more)	–0.2453	–2.356	0.0185	–0.0538
Commute Travel Time (1 if 0 to 9 minutes, 2 if 10 to 19 minutes, 3 if 20 to 34 minutes, 4 if 35 minutes or more)	0.1680	1.212	0.2256	0.0368
Model specification			Values	
Number of variables used			4	
Log-likelihood at zero,			–207.0385	
Log-likelihood at convergence			–200.8678	

χ2 value	12.3413
p-value	0.0224
Number of observations	326

4.2.2 Approach 2

An alternative approach was to estimate the coefficients of variables in the P&R utility function in the context of the coefficients of attributes for the existing modes. To accomplish this, the available dataset was used to implement the MNL model to get the estimated coefficients of attributes for the existing modes, namely, SOV, HOV and transit. Then, in order to obtain the coefficients of variables in the P&R utility function, a *weighted average* of the estimated transit and HOV coefficients (which were most similar modes to P&R) was used. The weight of estimated HOV coefficients in the P&R utility function is denoted by α. Consequently, ($1 - \alpha$) is the weight of transit coefficients.

4.3 Optimization Model

In this section, the incorporation of the MNL model into the optimization model is discussed and a MILP model is provided to find the optimal placement of P&R facilities.

4.3.1 Integrating Discrete Choice Model into MILP Model

In metropolitan cities like Nashville, there are a large number of commuters traveling from their residence to different points in the CBD area. It was assumed that these commuters have four options (modes) to reach to their destinations: SOV, HOV, transit, and P&R modes. As discussed earlier, P&R facilities give travelers the opportunity to use their own cars in the least congested part of the trip and then use public transit to complete their journey in the area that is most likely to be congested. Hence, these facilities can lead to a significant reduction in the traffic congestion in metropolitan areas.

Every commuter has different sensitivity to the travel time, travel comfort, or other attributes. Therefore, different commuters choose different modes or different P&R facilities based on their perceived utilities regarding each mode. In order to incorporate the preferences of commuters for selecting a mode of transport in the optimization model, the MNL model is used. Such a model can output the probability that commuter i chooses P&R facility k, SOV, HOV, or transit modes to travel to destination j. Note that one destination (CBD area) was considered in this study, hence, $j = 1$; however, the subscript j was not eliminated in the model provided in this report for completeness.

Commuters could select one mode of transport based on their utilities. The utility of using P&R k, and motorized modes (SOV, HOV, and transit modes) were denoted by g_{ijk} and g_{ijm}, respectively. The utility g_{ijk} included travel time in auto (SOV) for commuter i to P&R k (t_{ik}^{s}), transit time from P&R k to destination j (t_{kj}^{t}), and household and individual characteristic variables z_{il} (such as age, education, income, gender among others). In the utility g_{ijm}, the subscript $m \in M = \{s, h, t\}$ was considered, where m could be replaced by $s, h,$ and t indicating the SOV, HOV, and transit modes, respectively. The utility function g_{ijm} included travel time (t_{ij}^{m}), which was the time it took commuter i to reach to destination j by a motorized mode. In addition, it contained socioeconomic variables for commuter i denoted by z_{il} (such as age, education, income, gender among others). Note that because of the paucity of data, among alternative specific attributes, only travel time was considered in this report. In case of data availability, more alternative attributes such as parking fare in destination and P&R facilities, transit fare, waiting time in transit stations, transit frequencies, travel cost, travel distances, among others, could be added to the model to improve its accuracy. Equations (11)-(14) describe the utilities of motorized modes and P&R facility k:

$$g_{ijs} = \beta^s t_{ij}^s + \sum_l \gamma_l^s z_{il} \tag{11}$$

$$g_{ijh} = \beta^h t_{ij}^h + \sum_l \gamma_l^h z_{il} \tag{12}$$

$$g_{ijt} = \beta^t t_{ij}^t + \sum_l \gamma_l^t z_{il} \tag{13}$$

$$g_{ijk} = [\alpha\beta^h + (1-\alpha)\beta^t](t_{ik}^s + t_{kj}^t) + \sum_l [\alpha\gamma_l^h + (1-\alpha)\gamma_l^t] z_{il}\,, \tag{14}$$

where β^m and γ_l^m are the estimated coefficients of travel time and socioeconomic variables for each mode, respectively, obtained from logit models. In equation (14), α is the weight discussed in Section 4.2.2 and used for estimating the coefficients of features in the utility function of the P&R mode.

Based on the MNL model, the probability that the commuter i traveled to destination j using the P&R k or other modes was obtained by:

$$p_{ijl} = \frac{e^{g_{ijl}}}{\sum_{\forall l' \in K_1 \cup K_2 \cup M} e^{g_{ijl'}}} \qquad \forall l \in K_1 \cup K_2 \cup M. \tag{15}$$

Equation (15) was needed to incorporate the outputs of the MNL model into the optimization model. However, this equation could not be directly used in the optimization problem as it considered p_{ijl} for all candidate locations even if they were not available or established. Therefore, a binary location variable, denoted by x_k, was defined such that it assumed the value 1, if a P&R facility was located at site k, and assumed the value 0, otherwise. The set of all candidate locations for P&R facilities was denoted by K_1. Note that existing P&R facilities were also accounted for in the model. To do so, the binary variable x_k was set to always assume the value 1 for these existing facilities. The set of all existing facilities was denoted by K_2. The binary location variable x_l was incorporated in the MNL model as follows, which was set to 1 for existing P&R facilities, SOV, HOV, and transit modes:

$$p_{ijl} = \frac{x_l e^{g_{ijl}}}{\sum_{\forall l' \in K_1 \cup K_2 \cup M} x_{l'} e^{g_{ijl'}}} \qquad \forall l \in K_1 \cup K_2 \cup M. \tag{16}$$

In equation (16), the probability p_{ijl} was zero when the numerator was zero, which happened for those sites in which a P&R facility is not located ($x_l = 0$). Similarly, in the denominator, only those facilities that ware located were considered. Finally, equation (16) was added to the MILP model as a constraint to make the model more realistic and reliable.

Note that constraint (16) made the optimization problem nonlinear and hard to solve. In order to have a linear optimization problem, equation (16) was replaced with equations (17), (18) and (19):

$$p_{ijl} \le x_l \qquad \forall i,j\,,\ \forall l \in K_1 \cup K_2 \cup M \tag{17}$$

$$\textstyle\sum_{l \in K_1 \cup K_2 \cup M} p_{ijl} = 1 \qquad \forall i,j \tag{18}$$

$$p_{ijl} \le \frac{e^{g_{ijl}}}{e^{g_{ijl'}}} p_{ijl'} + (1 - x_{l'}) \qquad \forall i,j\,,\ \forall l,l' \in K_1 \cup K_2 \cup M\ |l \ne l' \tag{19}$$

4.3.2 Mathematical Formulation I (Maximizing Utilization)

This section presents a MILP formulation integrated with logit models to find the optimal locations of P&R facilities in the City of Nashville and its surrounding counties such that their usage is maximized. The notation used in the model are as follows:

Parameters:

i: Index of commuters

j: Index of destinations

K_1: Set of candidate P&R facilities

K_2: Set of existing P&R facilities

M: Set of motorized modes $\{s, h, t\}$, where s, h, and t indicate SOV, HOV, and transit modes

P: The total number of P&R facilities to be located

B: A very large number

Decision variables:

$$x_k = \begin{cases} 1 & \text{if a facility is located at site } k \\ 0 & \text{otherwise} \end{cases}$$

p_{ijl}: The probability that commuter i travels to destination j using mode l

The objective and constraints of the optimization model are as follows:

$$\max \sum_i \sum_j \sum_{l \in k_1 \cup k_2} p_{ijl} \tag{20}$$

Subject to:

$$p_{ijl} \leq x_l \qquad \forall i,j\,,\ \forall l \in K_1 \cup K_2 \cup M \tag{21}$$

$$\sum_{l \in K_1 \cup K_2 \cup M} p_{ijl} = 1 \qquad \forall i,j \tag{22}$$

$$p_{ijl} \leq \frac{e^{g_{ijl}}}{e^{g_{ijl'}}} p_{ijl'} + (1 - x_{l'}) \qquad \forall i,j\,,\ \forall l,l' \in K_1 \cup K_2 \cup M | l \neq l' \tag{23}$$

$$\sum_{l \in K_1} x_l \leq P \tag{24}$$

$$x_l = 1 \qquad \forall l \in K_2 \cup M \tag{25}$$

$$x_l \in \{0,1\} \qquad \forall l \in K_1 \cup K_2 \cup M \tag{26}$$

$$p_{ijl} \geq 0 \qquad \forall i,j\,, \forall l \in K_1 \cup K_2 \cup M \tag{27}$$

The objective function (20) maximized the proportion of trips using P&R facilities. Constraints (21)-(23) were equivalent to logit model constraint described earlier. Constraint (24) guaranteed that the total number of candidate P&Rs established was less than or equal to a predetermined constant P. Constraint (25) ensured that the binary variable x_l for existing P&R facilities, SOV, HOV, and transit were always set to one. Constraints (26) and (27) were integrality and non-negativity constraints.

4.3.3 Mathematical Formulation II (Minimizing Emissions)

In the previous section, a mathematical model with the objective of maximizing the usage of P&R facilities was formulated; however, in some cases, the objective may be to address environmental issues such as reduction in the level of emissions. Hence, in this section, an alternative mathematical formulation is presented that aims to reduce the total emissions.

In this model (mathematical formulation II), the goal was to find the optimal placement of P&R facilities to minimize the total amount of emissions:

$$\min\Big[\sum_i \sum_j \omega \times \tau_{ij} \times (p_{ijs} + p_{ijh}) + \sum_i \sum_j \sum_{k \in K_1 \cup K_2} \omega \times \tau_{ik} \times p_{ijk} + \sum_i \sum_j \sum_{k \in K_1 \cup K_2} \omega' \times \tau_{kj} \times p_{ijk} + \sum_i \sum_j \omega' \times \tau_{ij} \times p_{ijt}\Big] \tag{28}$$

s.t:

(21)-(27)

In the objective function (28), ω was the amount of emissions that each SOV/HOV vehicle produced per passenger mile, and ω' was the amount of emissions that bus transit produced per passenger mile. In addition, τ_{ij} was the distance that commuter i traveled to destination j. The first term of objective function (28) determined the total amount of emissions produced by SOV and HOV vehicles traveling between different origin-destination pairs. The second term calculated the amount of emissions released by SOV traveling to P&Rs. The third term identified the amount of emissions produced by transit services traveling to destination j. Finally, the last term specified the amount of emissions produced by transit services traveling from origin i to destination j.

4.4 TOD vs. P&R

Finally, TODs and P&Rs were compared in the City of Nashville to examine whether replacing a P&R facility with a TOD would reduce the vehicle kilometer traveled (VKT). Note that in this analysis, instead of evaluating P&R utilization, their contribution to VKT reduction was examined, which had a direct impact on reducing the negative impacts of automobile trips such as emissions.

Estimating the change in VKT after replacing a P&R facility with a TOD was accomplished through the following four steps (Duncan, 2019):

1. Estimating the average VKT reduction per P&R trip in each P&R facility.
2. Transforming the VKT reduction obtained in step 1 to VKT reduction per hectare in each P&R facility.
3. Specifying TOD characterizations that made the TOD comparable to a P&R in each location by using the VKT reduction per hectare estimated in step 2.
4. Evaluating whether the characterizations were realistic.

4.4.1 Average VKT Reduction per P&R Trip

The average VKT reduction per P&R round trip, denoted by R, was estimated as follows:

$$R = C - A \tag{29}$$

where A was the VKT generated during a P&R round trip (from origins to and from the P&R facility) and C was the VKT generated before that P&R facility was established.

Due to paucity of data, A and C were estimated using the following formula for each P&R facility k, i.e.,

$$A_k = 2 \times \frac{\sum_i \tau_{ik} \times P_{ik}}{\sum_i P_{ik}} \tag{30}$$

where P_{ik} was the probability that individual i chose P&R k and τ_{ik} was the distance between the origin and P&R facility k. In addition, based on the trip dataset, there were three available modes for commuters (before P&Rs) to travel to the CBD with mode shares of 59%, 34%, and 7% for SOV, HOV, transit. Hence, the following formula was used:

$$C_k = 2 \times \frac{\sum_i P_{ik} \times (0.59 \times D_{is} + 0.34 \times D_{ih} + 0.07 \times D_{it})}{\sum_i P_{ik}} \tag{31}$$

where D_{is}, D_{ih}, and D_{it} were the VKT generated by SOV, HOV, and transit modes, respectively. The VKT for SOV and HOV modes were then estimated using the distances between origins and CBD (τ_{is}). It was assumed that the VKT generated by HOV was half that of SOV, due to ridesharing. The VKT for transit was set to 0 ($D_{it} = 0$) as it was assumed that the distances between origins and transit stations were traversed on foot. Hence, equation (31) was simplified as follows:

$$C_k = 2 \times \frac{\sum_i P_{ik} \times (0.76 \times \tau_{is})}{\sum_i P_{ik}} \tag{32}$$

4.4.2 Average VKT Reduction per P&R Land Hectare

P&Rs and TODs compete for land, hence, to enable a fair comparison between the practices, the VKT reduction per land unit was used. To transform the unit of the VKT reduction per P&R trip to VKT reduction per hectare, the following formula was used:

$$RHP_k = \frac{\sum_i P_{ik}}{H_k} \times R_k \tag{33}$$

where RHP_k was the VKT reduction associated with each hectare of P&R k, and H_k was the amount of land (hectares) that was used for facility k. Due to paucity of data for the existing and candidate P&Rs in the City of Nashville, the same value for H was considered for all P&Rs. The value of H was estimated using the average of land hectares of P&Rs in the City of Charlotte, North Carolina (Duncan, 2019).

4.4.3 VKT Reduction for TODs

Finally, to estimate the VKT reduction for TODs (in terms of residential advancement), the following formula was used:

$$RHT_k = \left(\left(\frac{U_k}{H_k} \right) \times V \right) \times RT_k \tag{34}$$

where RHT_k was the VKT reduction per hectare for the TOD that was set to replace P&R k, U_k was the number of housing units to be built in place of P&R k, V was the vacancy rate in the built housing units (set to 10% (Duncan, 2019), and RT_k was the average VKT reduction per household after relocating to the TOD that was set to replace P&R k.

Chapter 5 Results and Discussion

5.1 Logit Models Results

Various experiments were conducted and the results of the MNL model, nested logit model, and mixed logit model after balancing the data were compared. For these comparisons, 10-fold cross validation was used, where the dataset was split into 10 non-overlapping subsets and in each fold, nine sets were used for model training and the resulting model was tested on the left-out set. Figure 3 illustrates an overview of the framework used in this report.

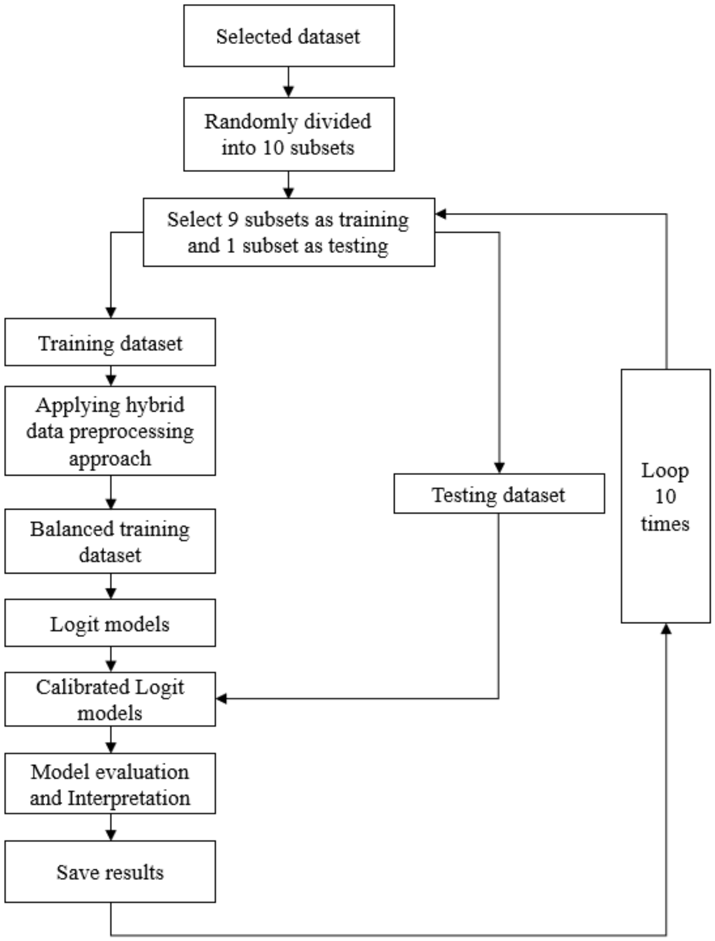

Figure 3. Overview of the applied framework in logit model results, adapted from (Rezaei et al., 2021).

Based on the results, MNL model was selected (for details, please refer to (Rezaei et al., 2021). Table XI presents the final mean and standard deviation of coefficients estimated by this model. This table shows that the output of the MNL model with balanced dataset is interpretable in terms of the sign of coefficients. For instance, travel time has a negative sign, implying that increasing the travel time of a mode reduces its attractiveness for commuters. In addition, the value of rho-squared shows the agreeable predictive capability of the resulting MNL model.

Table XI Estimated coefficients based on the MNL model calibrated on the balanced dataset

Alternative variables	
	Mean (SD)
SOV time	-0.01*** (0.00)
HOV Time	-0.01*** (0.00)
Transit Time	-0.03*** (0.00)

Individual variables					
	HOV	Transit		HOV	Transit
	Mean (SD)	Mean (SD)		Mean (SD)	Mean (SD)
Intercept	-2.01 *** (0.11)	1.57*** (0.27)	HH Retired Adults	-0.02 (0.04)	0.33*** (0.08)
Person Gender	0.12*** (0.02)	0.09 (0.04)	HH Other Adults	-0.002 (0.03)	0.08 (0.04)
Person Age	-0.01*** (0.00)	-0.01** (0.00)	HH College Students	-0.10*** (0.03)	-0.11** (0.08)
Person Type	0.34*** (0.01)	-0.16*** (0.02)	HH High School Students	-0.04 (0.02)	0.23*** (0.07)
Person Worker Type	-0.34*** (0.04)	0.09 (0.07)	HH Kids Age 5-15	0.15*** (0.03)	-0.10 (0.03)
Person Student Type	-0.2** (0.03)	0.19 (0.05)	HH Kids Age 0-4	0.18*** (0.04)	-0.41*** (0.05)
Paid Parking	-0.05 (0.04)	0.26*** (0.06)	HH Income	-4.6E-7** (2E-7)	-1E-5*** (2E-7)
HH Size	0.24*** (0.03)	0.07 (0.03)	HH Own or Rent	0.07 (0.02)	0.53*** (0.04)
HH Vehicles	-0.10*** (0.01)	-0.61*** (0.04)	HH Residence Type	-0.05 (0.01)	0.10** (0.02)
HH Workers	0.02 (0.04)	-0.03 (0.07)	Origin Purpose	0.04*** (0.00)	0.55*** (0.00)
HH Full Time Workers	0.02 (0.03)	-0.07 (0.06)	Destination Purpose	0.30*** (0.00)	-0.37*** (0.02)
HH part Time Workers	0.18*** (0.03)	0.14 (0.07)			
Rho-squared (Mean)				0.43	

** Significant at 95%; *** Significant at 99%

Note: SD = Standard deviation

5.2 Optimization Models Results

In this section, the results of the MILP model for a case study on the City of Nashville are provided. The learned coefficients reported in Section 5.1, Table XI, were used in the MILP model to find the optimal locations of P&R facilities to maximize the total number of riders that switch from SOVs to the public transit mode. All experiments were carried out on a desktop computer (Intel Core i7, 2.8 GHz). These experiments were programmed in Python 3, and Gurobi 9.1.1 was used as solver in Pyomo (Hart et al., 2017).

5.2.1 Data Preprocessing Step

Before implementing the MILP model, one additional data pre-processing step was needed. As noted earlier, one limitation of the available dataset was that it only included the "travel time" of the selected mode (HOV, SOV, or transit) for each individual and lacked the "travel time" for other alternative modes. Therefore, the dataset itself was leveraged to estimate these times. That is, the travel time of modes other than the selected mode for each individual was estimated by using trips that were made between the same origin-destination pairs by other individuals. These estimated times were then reviewed for their validity and relevance. In rare cases that the estimated times were found to be unreasonable, these values were manually recalculated and adjusted. For instance, the estimated travel time from "Murfreesboro" in the south east of Nashville to P&R 6 in the north of Nashville (see Figure 4) was too small and hence was modified to reflect a more realistic value.

In addition, in order to reduce the computational time of the optimization model, in each zone, "representatives" who presented the median characteristics of those individuals were identified. As a result, the demand was modified from 1 per individual to d_i in any given zone i and the objective function was modified as follows:

$$\max \sum_{i} \sum_{j} \sum_{l \in k_1 \cup k_2} d_i p_{ijl} \tag{35}$$

5.2.2 P&R Demand Estimation

As discussed in Sections 3 and 4.2, due to paucity of data, two approaches were advised to estimate the coefficients of the variables in the utility function of P&R modes in the MNL model. To examine the applicability of the approaches, small case studies were used. In the following, the results are presented. Per these results, ultimately Approach 2 was selected.

5.2.2.1 Approach 1

Two existing P&R facilities were considered in the Nashville area, denoted by P&R 1 and P&R 2 demonstrated in Figure 4, and the MNL model was implemented using the coefficients in (Cornejo et al., 2014). The results were not considered to be reasonable, as the coefficient obtained for travel time was positive. A positive coefficient for travel time indicates that travel time has a positive effect on the users' utility function, resulting in commuters to prioritize P&R 1 above else. Indeed, the results showed that from a total of 23,864 trips from different regions to CBD, 794, 23023, and 29 commuters used SOV, P&R 1 and P&R 2, respectively. In addition, the results showed that P&R 1 had demand from all regions (even those farther in the north of CBD), which did not seem realistic.

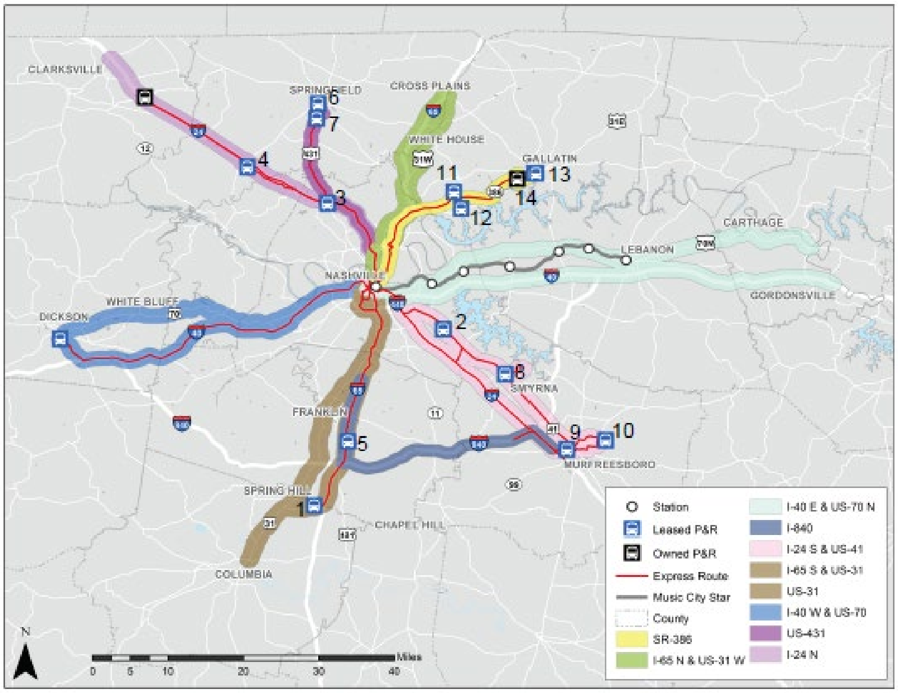

Figure 4. Existing P&R facilities in City of Nashville and its surrounding counties (WeGo Public Transit, 2020)

5.2.2.2 Approach 2

The existing P&Rs in the City of Nashville (as shown in Figure 4) were chosen to evaluate the results of Approach 2 and the degree to which they agreed with the current system in place regarding each level of α. As mentioned earlier, α and $(1 - \alpha)$ respectively denoted the weight of estimated HOV and transit coefficients in the P&R's utility function. Table XII presents the results of sensitivity analysis with respect to seven levels of α, i.e., α = 0.01, 0.15, 0.2, 0.35, 0.5, 0.7, 0.85. Specifically, the table shows the number of commuters who chose the mode k as estimated by $\sum_i \sum_j d_i p_{ijk}$. Note that the model output probabilities, indicating the probability that an individual selected a specific mode, were post-processed to increase the quality of the results. This included truncating the probabilities that were less than 0.02 by setting those to zero, and rescaling the remaining probabilities to ensure that the summation of probabilities remained one for each individual.

Table XII The usage of all modes in results of Approach 2 for P&R demand estimation

	$\alpha = 0.01$	$\alpha = 0.15$	$\alpha = 0.2$	$\alpha = 0.35$	$\alpha = 0.5$	$\alpha = 0.7$	$\alpha = 0.85$
SOV	9940	9666	9547	9114	8519	7367	6190
HOV	7185	6973	6879	6512	5978	4879	3759
Transit	2681	2782	2812	2870	2886	2799	2675
P&R 1	24	37	44	85	144	220	254
P&R 2	1115	1186	1218	1370	1612	1811	1660
P&R 3	1081	1083	1087	1143	1297	2033	1712

P&R 4	46	49	50	59	82	226	784
P&R 5	110	145	160	197	234	298	505
P&R 6	91	124	139	188	250	353	550
P&R 7	166	194	209	254	322	438	789
P&R 8	218	292	333	513	752	963	880
P&R 9	111	144	159	214	274	359	507
P&R 10	38	50	56	78	114	157	206
P&R 11	490	497	500	511	541	841	1190
P&R 12	275	306	318	354	398	522	905
P&R 13	129	150	160	188	217	280	595
P&R 14	164	186	193	214	244	318	703

Note: P&R = park-and-ride

As seen in Table XII, the usage of SOV and HOV generally decreased in α, while the usage of P&R facilities increased in α. This was because α determined the degree of similarity of the P&R mode to transit and HOV modes, and hence, by increasing (decreasing) α, the approach made the P&R mode more similar to the HOV (respectively, transit) mode. Hence, as α increased, the P&R mode more closely behaved like the HOV mode and it became a comparable mode to SOV and HOV, so more commuters chose it. Interestingly, as α increased, the usage of transit mode first increased and then decreased (after $\alpha = 0.5$). This was attributed to the fact when α was low, the transit mode and P&R mode were most similar and hence, they competed for commuters' attention. However, P&R mode, which had lower travel time than the transit mode had an advantage and attracted more commuters. In contrast, when α was large, all SOV, HOV and P&R modes were good options for commuters, and the transit mode, which generally had the highest travel time, lost its demand.

Table XIII presents the results from another perspective; the table shows the mode share based on SOV, HOV, transit and P&R modes. This table was used to choose a reasonable α for the rest of the experiments in this report. As this table presents, when α was greater than 0.5 or between 0.35 and 0.5, the usage of P&Rs was greater than or relatively comparable to the SOV mode, respectively. Because these were inconsistent with the observations made from the City of Nashville, a smaller α was selected. The results were relatively consistent when α = 0.01, 0.15 and 0.2. Hence, to avoid allowing a very low α that heavily skewed the P&R mode toward transit in the remainder of the analysis, α = 0.2 was chosen.

Table XIII The share of each mode in results of Approach 2 for P&R demand estimation

	$\alpha = 0.01$	$\alpha = 0.15$	$\alpha = 0.2$	$\alpha = 0.35$	$\alpha = 0.5$	$\alpha = 0.7$	$\alpha = 0.85$
SOV	41.65%	40.5%	40.01%	38.19%	35.7%	30.87%	25.94%
HOV	30.11%	29.22%	28.83%	27.29%	25.05%	20.45%	15.75%
Transit	11.23%	11.66%	11.78%	12.03%	12.09%	11.73%	11.21%

P&R	17.01%	18.62%	19.38%	22.49%	27.16%	36.95%	47.1%

Note: P&R = park-and-ride

Figure 5 presents the share of commuters in each of the 12 regions in the Nashville area who chose to use P&R 1, P&R 2, and P&R 3 to travel to the CBD area under $\alpha = 0.2$. The number of commuters in each region who used P&R 1, P&R 2, and P&R 3 were denoted by K_1, K_2, and K_3, respectively. As seen in the figure, these three P&Rs only served the nearby origins. For instance, consider P&R 3. As seen in the figure, the number of commuters in each region who used this facility, denoted by K_3, were reasonable as positive values were observed only for the surrounding areas of Robertson, Sumner, North, Far NE, and West.

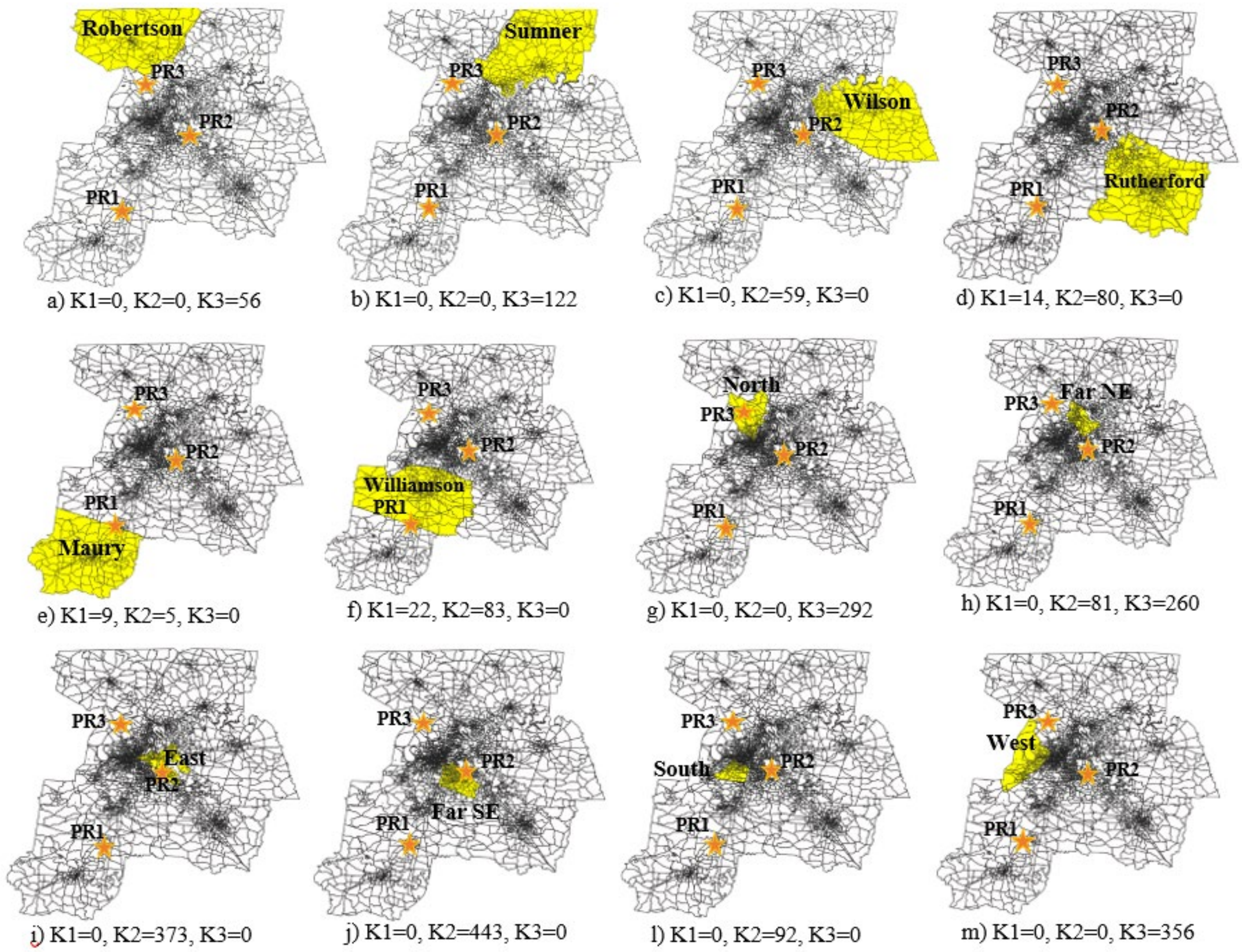

Figure 5. The results of the Approach 2 with $\alpha = 0.2$ for a case study for the City of Nashville when all existing P&Rs are considered. Note that *K1*, *K2*, and *K3* denote the number of commuters in each region who use PR1, PR2 and PR3, respectively, to travel to CBD area. [PR: park-and-ride]

5.2.3 Candidate P&R locations Evaluation

In this section, the results of the optimization model are presented. The dataset in Table IX was used for the analysis, which included all trips by SOV, HOV, and transit from Far areas and six counties around Nashville to the CBD area during the morning rush hour. This dataset was used for implementing the MNL model and obtained a demand model for the available modes, where Approach 2 was used with $\alpha = 0.2$ based on the results of Section 5.2.2. After deriving the

P&R coefficients, the integrated optimization model in Section 4.3 was implemented to obtain the optimal locations among a set of candidate locations in the City of Nashville.

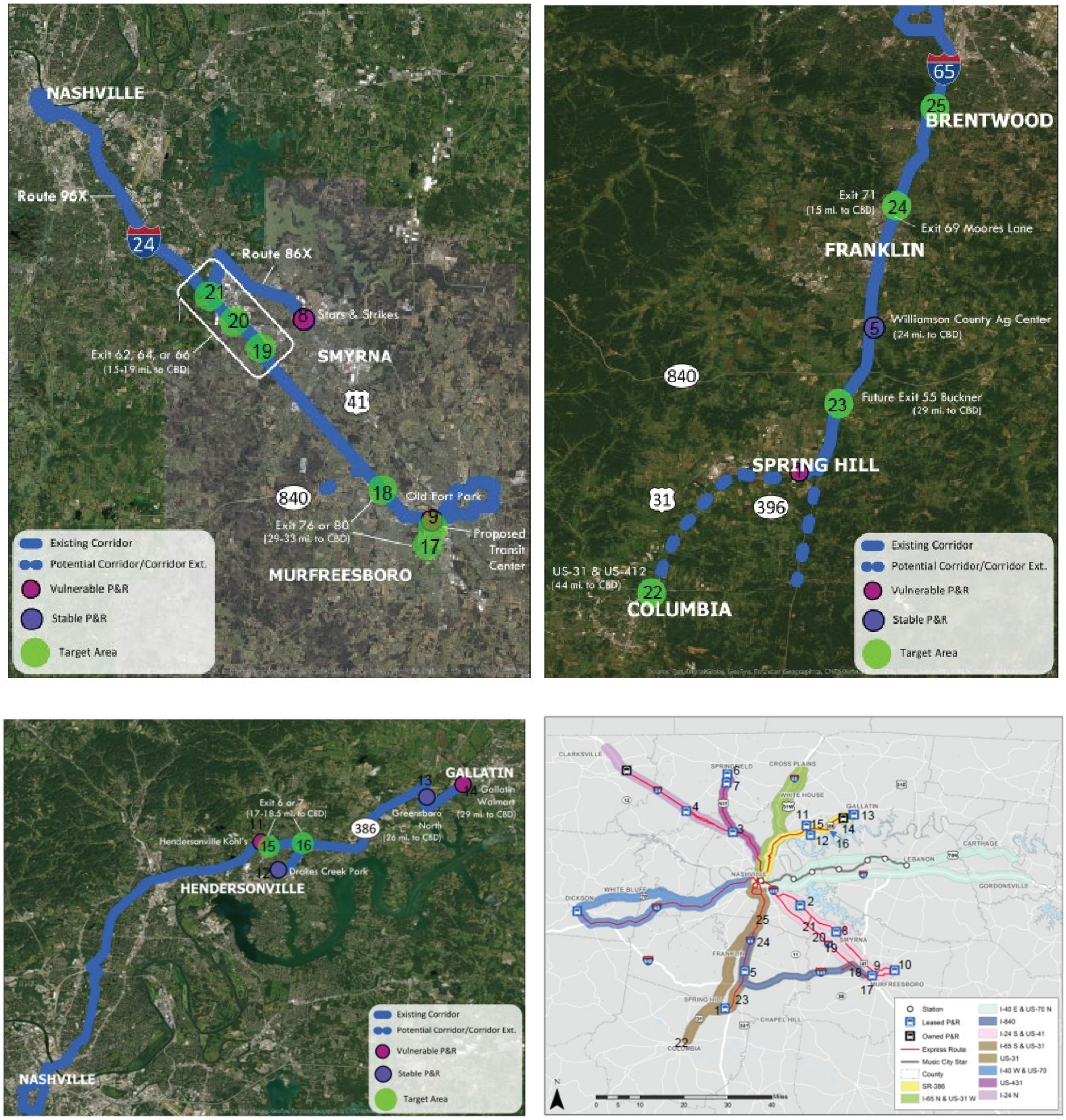

Figure 6. Maps of main corridors and the candidate P&R locations in the Nashville area. The figure shows I65 South/US 31 (top right), I-24 South/US 41 (top left), SR 386 (bottom left), and all corridors (bottom right) (WeGo Public Transit, 2020)

Based on WeGo Park & Ride Strategic Investment Plan report (WeGo Public Transit, 2020), 11 candidate locations in were considered in the evaluations. In this report, first, the main corridors in the City of Nashville were prioritized for investment based on five characteristics, including distance to CBD, amount of commuter traffic travelling to the CBD, population density, expected population growth, and congestion. Based on these characteristics, the top three corridors in no particular order were identified as I65 South/US 31, I-24 South/US 41, and SR 386. Next, the candidate locations were determined on these corridors. Figure 6 presents these top three corridors and the corresponding candidate locations, demonstrated as green circles. Based on WeGo Park & Ride Strategic Investment Plan report, in I65 South/US 31, one new P&R could be established on one of the two candidate locations 17 and 18. Furthermore, among the three candidate locations 19, 20 and 21, one must be selected to eventually replace the existing P&R 8. Next, in I-24 South/US 41, candidate locations 23 and 24 were introduced to replace the existing P&R 1 and P&R 5. In addition, two additional candidate locations 22 and 25 were also introduced in this corridor. Lastly, in SR 386, one P&R facility must be established in candidate locations 15 and 16 to eventually replace with P&R 12.

5.2.3.1 In the Absence of Constraints on Placement of P&Rs

First, all these existing and candidate P&R locations were considered and the optimization model was implemented to select 2 and 5 locations from these 11 candidate locations ($P = 2$ and $P = 5$). That is, in this analysis, the current suggestions made regarding the placement/ replacement of candidate and existing P&Rs were not considered. Tables XIV and XV present the detailed results of the optimization model based on each area in City of Nashville for $P = 2$ and $P = 5$, respectively.

As seen in Table XIV, when the goal was to establish only two P&Rs ($P = 2$), candidate locations 21 and 25 were recommended by the model. The results showed that candidate location 21 had 328, 242, 101, 94, 58 and 6 demand from Far SE, East, Rutherford, Williamson, Wilson and Maury, respectively, and candidate location 25 served 340, 198, 148, 119, 43 and 6 commuters from Far SE, East, Williamson, South, Rutherford and Maury, respectively.

As seen in Table XV, when the goal was to establish five P&Rs ($P = 5$), candidate locations 15, 19, 20, 21, and 25 were recommended by the model. The results suggested that the model prioritized locations mostly based on their proximity to the CBD area (as inferred by travel times). This was expected as 'travel time' was the only alternative specific attribute considered in the model.

Table XVI presents results of the optimization model based on each mode share, when all existing and candidate P&Rs were considered. The goal of this experiment was to analyze the impact of parameter P (which determined how many P&R facilities could be established) on the mode share. As seen in the table, as P increased, the share of P&R facilities increased and consequently, the share of transit, SOV and HOV decreased. This showed that adding more facility allowed to cover more demand and encouraged more commuters to use P&R facilities.

Table XIV Optimization model results with all existing and candidate P&Rs when $\boldsymbol{P} = \mathbf{2}$

$P = 2$	Robertson	Sumner	Wilson	Rutherford	Maury	Williamson	North	FarNE	East	FarSE	South	West
SOV	201	567	472	359	45	974	779	621	1167	1491	959	1284
HOV	139	365	419	413	52	773	725	410	899	1078	482	780
Transit	10	70	84	41	13	85	372	205	729	403	159	390
P&R 1	0	0	0	9	8	15	0	0	0	0	0	0
P&R 2	0	0	57	67	4	60	0	83	282	323	71	0
P&R 3	56	122	0	0	0	0	294	261	0	0	0	367
P&R 4	47	0	0	0	0	0	0	0	0	0	0	0
P&R 5	0	0	0	42	8	76	0	0	0	0	0	0
P&R 6	33	43	0	0	0	0	65	0	0	0	0	0
P&R 7	47	68	0	0	0	0	94	0	0	0	0	0
P&R 8	0	0	15	60	1	9	0	0	53	85	0	0
P&R 9	0	0	24	79	4	26	0	0	0	0	0	0
P&R 10	0	0	4	41	1	0	0	0	0	0	0	0
P&R 11	37	179	74	0	0	0	0	207	0	0	0	0
P&R 12	21	120	39	0	0	0	0	136	0	0	0	0
P&R 13	15	93	49	0	0	0	0	0	0	0	0	0
P&R 14	21	117	52	0	0	0	0	0	0	0	0	0
P&R 15	0	0	0	0	0	0	0	0	0	0	0	0
P&R 16	0	0	0	0	0	0	0	0	0	0	0	0
P&R 17	0	0	0	0	0	0	0	0	0	0	0	0
P&R 18	0	0	0	0	0	0	0	0	0	0	0	0
P&R 19	0	0	0	0	0	0	0	0	0	0	0	0
P&R 20	0	0	0	0	0	0	0	0	0	0	0	0
P&R 21	0	0	58	101	6	94	0	0	242	328	0	0
P&R 22	0	0	0	0	0	0	0	0	0	0	0	0
P&R 23	0	0	0	0	0	0	0	0	0	0	0	0
P&R 24	0	0	0	0	0	0	0	0	0	0	0	0
P&R 25	0	0	0	43	6	148	0	0	198	340	119	0

Note: ‘P&R’ represents both candidate and existing P&Rs

Table XV Optimization model results with all existing and candidate P&Rs when $\boldsymbol{P} = \mathbf{5}$

$P = 5$	Robertson	Sumner	Wilson	Rutherford	Maury	Williamson	North	FarNE	East	FarSE	South	West
SOV	189	516	426	313	42	921	774	567	1068	1347	954	1277
HOV	132	335	385	369	50	738	722	381	848	1005	480	777
Transit	10	62	73	33	12	79	369	180	663	357	158	386
P&R 1	0	0	0	5	7	12	0	0	0	0	0	0
P&R 2	0	0	49	55	4	51	0	72	250	280	74	0
P&R 3	53	111	0	0	0	0	297	232	0	0	0	382
P&R 4	44	0	0	0	0	0	0	0	0	0	0	0
P&R 5	0	0	0	33	8	67	0	0	0	0	0	0
P&R 6	31	34	0	0	0	0	69	0	0	0	0	0
P&R 7	44	61	0	0	0	0	98	0	0	0	0	0
P&R 8	0	0	10	50	1	5	0	0	39	61	0	0
P&R 9	0	0	17	67	3	19	0	0	0	0	0	0
P&R 10	0	0	2	30	0	0	0	0	0	0	0	0
P&R 11	35	161	65	0	0	0	0	183	0	0	0	0
P&R 12	20	109	32	0	0	0	0	119	0	0	0	0
P&R 13	14	85	40	0	0	0	0	0	0	0	0	0
P&R 14	20	105	45	0	0	0	0	0	0	0	0	0
P&R 15	36	165	67	0	0	0	0	188	0	0	0	0
P&R 16	0	0	0	0	0	0	0	0	0	0	0	0
P&R 17	0	0	0	0	0	0	0	0	0	0	0	0
P&R 18	0	0	0	0	0	0	0	0	0	0	0	0
P&R 19	0	0	42	95	6	70	0	0	146	181	0	0
P&R 20	0	0	42	90	5	71	0	0	173	234	0	0
P&R 21	0	0	51	83	5	85	0	0	212	284	0	0
P&R 22	0	0	0	0	0	0	0	0	0	0	0	0
P&R 23	0	0	0	0	0	0	0	0	0	0	0	0
P&R 24	0	0	0	0	0	0	0	0	0	0	0	0
P&R 25	0	0	0	33	5	141	0	0	171	298	122	0

Note: 'P&R' represents both candidate and existing P&Rs

Table XVI The mode share in the results of the optimization model considering all existing and candidate P&Rs

	$P = 0$	$P = 1$	$p = 2$	$P = 5$	$P = 8$
SOV	40.01%	39.36%	37.38%	35.18%	34.12%
HOV	28.83%	28.45%	27.39%	26.08%	25.42%
Transit	11.78%	11.59%	10.73%	9.98%	9.66%
P&R	19.38%	20.59%	24.50%	28.76%	30.80%
Selected P&R	-	15	21-25	15-19-20-21-25	15-16-18-19-20-21-24-25

Note: 'P&R' represents both candidate and existing P&Rs

5.2.3.2 When Accounting for Constraints on Placement of P&Rs

Next, experiments were conducted while incorporating constraints on the placement of P&Rs. Specifically, as previously discussed, prior recommendations per WeGo Park & Ride Strategic Investment Plan report were considered (WeGo Public Transit, 2020). In order to incorporate these assumptions into the MILP model, the following constraints were added in place of constraint (24):

$$x_{12} + x_{15} + x_{16} = 1 \tag{36}$$

$$x_1 + x_5 + x_{23} + x_{24} = 2 \tag{37}$$

$$x_{22} + x_{25} \leq 2 \tag{38}$$

$$x_{17} + x_{18} = 1 \tag{39}$$

$$x_8 + x_{19} + x_{20} + x_{21} = 1 \tag{40}$$

Constraint (36) guaranteed that one and only one location was selected out of candidate locations 15 and 16 and the existing P&R 12. Constraint (37) allowed for evaluating whether any of the candidate locations 23 and 24 should replace the existing P&Rs 1 and 5. Inequality (38) allowed up to two additional P&Rs to be established in locations 22 and 25 (this redundant constraint is only presented for completeness). Constraint (39) guaranteed that one and only one of the candidate locations 17 and 18 should be opened. Finally, constraint (40) helped to evaluate whether a candidate location among 19, 20 and 21 should replace the existing P&R 8.

Table XVII presents the optimization model results. The results showed that candidate location 15 was recommended to be established to replace the existing P&R 12. The model recommended to establish the candidate location 24 in place of the existing P&R 1; however, it did not select candidate location 23 and opted to keep the existing P&R 5 open. Although the model picked both candidate locations 22 and 25, the usage of location 22 was rather small (as it is far away from CBD area). Hence, this location did not seem to be desirable for commuters when only "travel time" was considered. In addition, model chose candidate location 18 over location 17. Lastly, candidate location 21 was chosen to replace the existing P&R 8.

Table XVII Optimization model results to evaluate replacing existing P&Rs with candidate locations

	Usage	X
SOV	8772	1
HOV	6445	1
Transit	2515	1
P&R 1	0	0
P&R 2	913	1
P&R 3	1091	1
P&R 4	46	1
P&R 5	111	1
P&R 6	139	1
P&R 7	207	1
P&R 8	0	0
P&R 9	119	1
P&R 10	42	1
P&R 11	474	1
P&R 12	0	0
P&R 13	149	1
P&R 14	182	1
P&R 15	488	1
P&R 16	0	0
P&R 17	0	0
P&R 18	148	1
P&R 19	0	0
P&R 20	0	0
P&R 21	795	1
P&R 22	6	1
P&R 23	0	0
P&R 24	407	1
P&R 25	817	1

Note: "P&R" represents both candidate and existing P&Rs

5.2.4 Sensitivity Analysis

Sensitivity analysis is a systematic approach for evaluating the impact of variations in inputs, assumptions, or the manner in which the model is set up on the outcome of that model. In other words, this approach allows for identifying the degree to which the results are sensitive to changes in model parameters and set-up. This can draw attention to the modeling choices made or the need for improving the estimation of particular parameters with respect to which the results may be sensitive. In this section, the sensitivity of the optimal location of candidate P&Rs to travel time, traffic flow, and population growth is investigated using a series of scenarios, and then the impact of the choice of the objective function is examined on the results.

5.2.4.1 Sensitivity to Travel Time, Traffic Flow, and Population Growth

Travel time, traffic flow, and population growth are all important considerations in the proposed MILP model. Clearly, travel time and traffic flow are correlated, and population growth can impact both. For instance, if metro area population grows, but the road infrastructure is not improved, traffic flow is expected to be negatively affected, leading to an increase in travel time. This can be mitigated using a series of actions such as adding new lanes to freeways, applying a signal coordination strategy for faster travel along particular corridors, and improving transit frequency and reliability, to name a few.

Overall, 11 hypothetical scenarios were considered to examine the impact of the changes in inputs on the model recommendations. A medium-term view was adopted to incorporate the impact of population growth and potential investments in the road infrastructure (see Figure 7). Specifically, three cases were considered for the population growth: No changes; 20% growth across the board; and 60% for Williamson and 20% for other areas. This could clearly impact the travel time for all modes (transit, HOV, SOV). Consequently, cases were considered where transit time was improved to various degrees, e.g., due to establishing an express bus lane or increasing transit frequency.

Figure 7 illustrates the scenarios considered. In scenarios 1-3, no population growth was assumed and transit time was improved. Hence, SOV and HOV travel times did not change, but transit time decreased to various degrees. In scenarios 4-6, it was assumed all travel times increased due to population growth and no transit time improvement. In scenarios 7-8, transit time was slightly improved, compared with 4-6, due to potential investments. In scenarios 9-10, it was assumed that transit time only decreased for the I-65 corridor. Finally, in scenario 11, it was assumed that 'Williamson' county had an increased population growth, compared with other areas, hence, despite an investment to lower the transit time, compared with scenario 10, it showed a lower reduction in transit time.

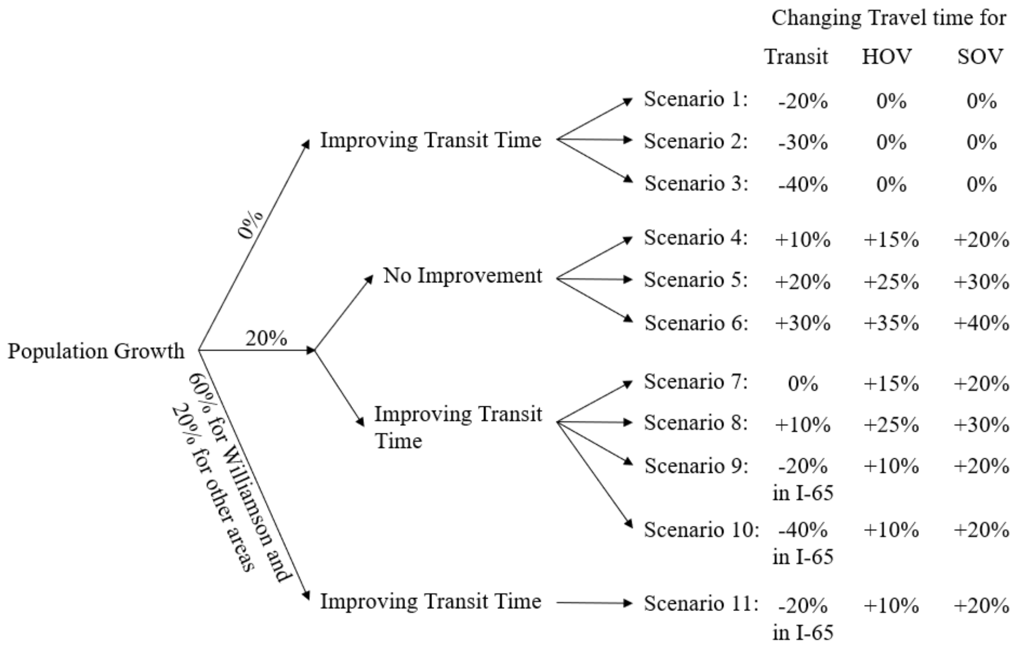

Figure 7. Different scenarios based on potential changes in population growth and transit improvement

Table XVIII presents results of the optimization model for these 11 scenarios, when the maximum number of candidate locations to be established is 5 ($P = 5$). As seen in the table, the selected P&Rs in scenarios 1-8 are the same (15-19-20-21-25). This is reasonable as in all these scenarios, it was assumed that the changes to the system (e.g., population growth and/or rate of change in travel time) impacted all regions consistently. Note that in scenario 9, the solution remained the same, even though in this scenario the transit time through I-65 was disproportionately reduced. This was because the amount of this reduction was not enough to encourage the model to choose any other candidate locations in this corridor. In scenario 10, where the transit time was further reduced, the solution indeed changed to replace P&R 15 with P&R 24, which was located in corridor I-65, to take advantage of the reduced travel time. Lastly, despite the same travel times, due to disproportionate population growth across regions in scenario 11 compared with scenario 9, the model opted for P&R 24 instead of P&R 19.

Table XVIII also presents the share of SOV, HOV, transit, and P&R modes in these 11 scenarios. As seen in the table, mode shares are generally not very sensitive to the changes in scenarios. However, the results showed certain trends. For instance, as expected, in general, the usage of P&R and transit modes increased with reduction in transit time (see scenarios 1-3 and in scenario pairs of (4, 7) and (5, 8)). However, when travel times across all modes increased, the share of P&R and transit decreased, while the share of SOV and HOV increased (see scenarios 4-6). This suggested that commuters opted for generally faster modes when all travel times were generally large.

Table XVIII Results of the optimization model for different scenarios that are based on variations in transit time and population growth, when $\boldsymbol{P = 5}$

	SOV	HOV	Transit	P&R	Selected P&Rs
Scenario 1	31.91%	24.14%	11.72%	32.23%	15-19-20-21-25
Scenario 2	30.22%	23.13%	12.73%	33.92%	15-19-20-21-25
Scenario 3	28.48%	22.07%	13.85%	35.6%	15-19-20-21-25
Scenario 4	34.50%	27.52%	9.48%	28.50%	15-19-20-21-25
Scenario 5	34.91%	28.65%	8.90%	27.54%	15-19-20-21-25
Scenario 6	35.25%	29.78%	8.38%	26.59%	15-19-20-21-25
Scenario 7	32.99%	26.56%	10.24%	30.21%	15-19-20-21-25
Scenario 8	33.46%	27.69%	9.60%	29.25%	15-19-20-21-25
Scenario 9	32.62%	26.53%	10.12%	30.73%	15-19-20-21-25
Scenario 10	32.10%	26.15%	9.89%	31.86%	19-20-21-24-25
Scenario 11	32.74%	26.79%	9.86%	30.62%	15-20-21-24-25

Note: P&R represents both candidate and existing P&Rs

5.2.4.2 Sensitivity to Objective Function

The MILP model was re-executed under the emission reduction objective function introduced in Section 4.3.3. To estimate the requisite distances from different origins to P&R facility k (τ_{ik}), travel times and average speed between origin-destination pairs were used.

Table XIX provides the share of each mode when considering emission reduction as the objective as a function of the number of established P&Rs, P. It was interesting to note that the solutions under this objective function (emission minimization) generally differed with those under the utilization maximization objective function, except for when P = 8 (see Table XVI); when a maximum of 8 candidate P&Rs had to be selected (P = 8), the MILP model identified the same candidate P&Rs under both objective functions. This was because P&R facilities 17, 22 and 23, which were not selected, were in the farthest areas from CBD and hence, were unfavorable with respect to both objective functions. Furthermore, note that although the sets of selected P&Rs were generally different under the two objective functions, their usages and mode shares were rather similar, implying that the MILP model with emission reduction objective function indeed improved P&R utilization to a great extent.

Table XIX The mode share in the results of the MILP model considering emission reduction objective function

	$P = 0$	$P = 1$	$p = 2$	$P = 5$	$P = 8$
SOV	40.04%	39.50%	38.04%	35.42%	34.12%
HOV	28.85%	28.53%	27.70%	26.24%	25.42%
Transit	11.79%	11.63%	11.04%	10.10%	9.67%
P&R	19.32%	20.34%	23.22%	28.24%	30.79%
Selected P&R	-	16	15-21	15-16-20-21-25	15-16-18-19-20-21-24-25

Note: 'P&R' represents both candidate and existing P&Rs

5.3 TOD vs. P&R

Finally, TODs and P&Rs were compared in the City of Nashville.

5.3.1 Average VKT Reduction per P&R Trip

Table XX provides the input parameters and results of the average VKT reduction for the P&R round trip for each facility. Note that P_{ik} was obtained by the MILP model, where P = 2, under both objective functions (utilization maximization and emission reduction). The estimated average VKT reduction in both cases ranged from 1 to 90 kilometers, where the reduction was generally more pronounced under the emission reduction objective function (i.e., 32.5 vs. 20.3 in VKT reduction). This was consistent with intuition as minimizing the emission reduction implicitly reduced the VKT at the same time. Thus, the emission reduction objective function was used for the remainder of the experiments to examine the VKT reduction of P&R facilities under the more favorable setting.

Table XX Average VKT reduction per P&R trip, where P = 2, under both utilization maximization and emission reduction objective functions.

UM	C_k	H_k	R_k	ER	C_k	A_k	R_k
P&R 1	134.6	55.0	79.7	P&R 1	131.6	56.6	75.0
P&R 2	50.7	29.6	21.0	P&R 2	49.4	29.1	20.3
P&R 3	47.5	46.3	1.2	P&R 3	46.8	46.2	0.60
P&R 4	117.1	45.8	71.2	P&R 4	116	44.6	71.4
P&R 5	105.2	51.4	53.9	P&R 5	103	50.8	52.2
P&R 6	71	61.8	9.1	P&R 6	68.6	61.3	7.3
P&R 7	71.3	60.6	10.7	P&R 7	69.8	60.6	9.2
P&R 8	68.6	38.7	29.9	P&R 8	65.3	39.1	26.1
P&R 9	114.7	54.6	60.1	P&R 9	114	54.3	59.7
P&R 10	125.1	37.8	87.4	P&R 10	124.8	37.8	87.0
P&R 11	75.9	34.3	41.7	P&R 11	76.5	34.7	41.7
P&R 12	75.6	34.4	41.2	P&R 12	76.2	34.8	41.5
P&R 13	100.9	45.8	55.1	P&R 13	101.4	45.7	55.7
P&R 14	99.1	44.6	54.5	P&R 14	99.4	44.9	54.4
P&R 21	58.0	33.8	24.2	P&R 15	76.5	34.7	41.8
P&R 25	47.30	31.0	16.3	P&R 21	56.7	33.5	23.2
ER&R	89.8	45.8	44.1		88.8	45.8	43
CP&R	52.7	32.4	20.3		66.6	34.1	32.5

EP&R: Existing P&R, CP&R: Candidate P&R, UM: Utilization Maximization, ER: Emission Reduction

5.3.2 Average VKT Reduction per P&R Land Hectare

Table XXI presents the inputs and result of the VKT reduction associated with each hectare of P&R for each facility. The estimated VKT reduction per hectare ranged widely across the facilities. The existing P&Rs 2 and 11, and the candidate P&Rs 15 and 21 had the highest VKT reduction per hectare compared with other facilities. In addition, the average VKT reduction for candidate locations was much larger than that of the existing P&R facilities.

Table XXI Average VKT per land hectare, where *P* = 2, under the emission reduction objective function

UM	$\sum_i P_{ik}$	H_k	R_k	RHP_k
P&R 1	37.3	1.26	79.7	2218.2
P&R 2	1057.9	1.26	21.0	17070.7
P&R 3	1055.3	1.26	1.2	519.5
P&R 4	46.4	1.26	71.2	2632.0
P&R 5	140.8	1.26	53.9	5833.0

P&R 6	130.8	1.26	9.1	758.9
P&R 7	200.1	1.26	10.7	1459.6
P&R 8	260.1	1.26	29.9	5396.6
P&R 9	137.7	1.26	60.1	6523.1
P&R 10	47.9	1.26	87.4	3309.3
P&R 11	446.1	1.26	41.7	14771.6
P&R 12	282.1	1.26	41.2	9283.6
P&R 13	141.8	1.26	55.1	6269.8
P&R 14	173	1.26	54.5	7473.6
P&R 15	458.2	1.26	24.2	15185.3
P&R 21	926	1.26	16.3	17052.7
ER&R	296.95	1.26	44.1	5965.7
CP&R	692.1	1.26	20.3	16119.0

EP&R: Existing P&R, CP&R: Candidate P&R, UM: Utilization Maximization, ER: Emission Reduction

5.3.3 VKT Reduction for TODs and Evaluations

To justify the replacement of a P&R facility with a TOD, the VKT reduction per hectare for TOD should match or exceed that of the P&R. Therefore, TOD characteristics (residential density (U/H) and RT) could be estimated to meet targeted VKT reductions. However, it is important to note that these characteristics must be evaluated to ensure their feasibility (e.g., permitted residential density in the area per regulations and guidelines, etc.).

Two sets of analysis were performed. First, the residential density (U/H) was fixed to find the minimum average VKT reduction per household after relocating to the TOD (RT) that allowed for meeting the corresponding RHP. Next, RT was fixed to find the minimum residential density (U/H) that allowed for meeting the corresponding RHP. Table XXII provides the results of the first analysis, under different levels of U/H, ranging from 50-400 units/ha. Table XXIII provides the results of the second analysis, under different levels of RT, ranging from 5-40 VKT/hh.

Based on the study in (Duncan, 2019) conducted in the City of Charlotte, NC, reaching the VKT target becomes less realistic if the minimum density is larger than 100 units per hectare or if the average VKT per household should reduce more than 20 VKT per day. According to these characteristics, it was concluded that TOD at existing P&R facilities 3, 6 and 7 could meet the targeted VKT reduction. For instance, although P&R 3 generally had high utilization, the VKT reduction per P&R trip for this facility was relatively small. This was because mostly commuters from “Far NE” and “Far West” areas, which were rather close to the CBD, chose this P&R. Hence, the RHP in this facility was rather low, making it a good candidate for a TOD. In contrast, for instance, candidate locations 15 and 21 were both well utilized and had large VKT reduction per trip, making them less ideal for TODs.

Table XXII Minimum average VKT reduction per household needed for the TOD to meet the target VKT reduction per P&R land hectare under different levels of residential density

	50 units/ha	100 units/ha	150 units/ha	200 units/ha	250 units/ha	300 units/ha	350 units/ha	400 units/ha
P&R 1	49	25	16	12	10	8	7	6
P&R 2	379	190	126	95	76	63	54	47
P&R 3	12	6	4	3	2	2	2	1
P&R 4	58	29	19	15	12	10	8	7
P&R 5	130	65	43	32	26	22	19	16
P&R 6	17	8	6	4	3	3	2	2
P&R 7	32	16	11	8	6	5	5	4
P&R 8	120	60	40	30	24	20	17	15
P&R 9	145	72	48	36	29	24	21	18
P&R 10	74	37	25	18	15	12	11	9
P&R 11	328	164	109	82	66	55	47	41
P&R 12	206	103	69	52	41	34	29	26
P&R 13	139	70	46	35	28	23	20	17
P&R 14	166	83	55	42	33	28	24	21
P&R 15	337	169	112	84	67	56	48	42
P&R 21	379	189	126	95	76	63	54	47

ha: hectare

Table XXIII Minimum housing units per hectare needed for the TOD to meet the target VKT reduction per P&R land hectare under different levels of VKT reduction per household

	5 VKT/hh	10 VKT/hh	15 VKT/hh	20 VKT/hh	25 VKT/hh	30 VKT/hh	35 VKT/hh	40 VKT/hh
P&R 1	493	246	164	123	99	82	70	62
P&R 2	3793	1897	1264	948	759	632	542	474
P&R 3	115	58	38	29	23	19	16	14
P&R 4	585	292	195	146	117	97	84	73
P&R 5	1296	648	432	324	259	216	185	162
P&R 6	169	84	56	42	34	28	24	21
P&R 7	324	162	108	81	65	54	46	41
P&R 8	1199	600	400	300	240	200	171	150
P&R 9	1450	725	483	362	290	242	207	181
P&R 10	735	368	245	184	147	123	105	92
P&R 11	3283	1641	1094	821	657	547	469	410
P&R 12	2063	1032	688	516	413	344	295	258
P&R 13	1393	697	464	348	279	232	199	174
P&R 14	1661	830	554	415	332	277	237	208
P&R 15	3375	1687	1125	844	675	562	482	422
P&R 21	3789	1895	1263	947	758	632	541	474

hh: household

5.4 Discussion

The developed models are capable of prescribing the optimal locations of P&R facilities and evaluating the potential benefits of introducing TODs in the network. However, before the proposed framework's recommendations can be used in practice, appropriate data must be collected, and all modeling choices and assumptions must be carefully considered.

In this section, the results are discussed, the significance of the findings is elaborated upon, and the limitations and future work are provided. The first major set of results concerns the optimal locations of P&R facilities, prescribed by the MILP model, among a set of 11 candidate P&R facilities. These candidate facilities are generally located in three main corridors in the City of Nashville. As seen in the results, the MILP model typically choose the closest P&Rs (as inferred by travel times) to the CBD area. This is expected given the available data because the only alternative specific variable that is considered in the model is 'travel time.' Hence, care must be taken before using the results of this model for strategic placement of P&R facilities. Arguably, attributes other than travel time can play a role in making P&Rs attractive to commuters, e.g., these include 'travel cost,' 'transit frequency,' 'parking fare,' etc. Hence, data about these attributes and preferences of commuters towards them should be included to ensure that the model's recommended solutions are most realistic.

The second major set of results concerns the outputs of the sensitivity analysis, which show that the model is sensitive to certain parameters, such as travel time, traffic flow, and population growth, and the choice of the objective function. Hence, these parameters need to be accurately estimated/projected to ensure that the results of the model are applicable in practice. In addition, the objective function, along with other potential constraints, must be carefully selected to ensure that the results are in line with the strategic goals for the city and state.

The last major set of results concerns the potential introduction of TODs in the network. As seen in the results, only three existing P&Rs are considered to be potential candidates to be replaced with TODs. All these three existing P&Rs are located in the US-431corridor. One of these identified P&Rs has high utilization, but provides low VKT reduction, and is hence selected as a candidate. The other two are mainly selected due to their relatively low utilization. However, additional analysis is required before replacing these P&Rs with TODs. First, these recommendations are solely based on a limited set of feasible characteristics of TOD (including residential density and VKT reduction per household). Second, in the analysis, the vacancy rate in the VKT reduction per hectare is assumed to be 10%, which may need to be further investigated and validated. Hence, future work remains as to identify all feasible ranges of TOD characteristics and obtain more accurate estimation of vacancy rates in all locations.

In summary, the developed models are capable of prescribing the optimal locations of P&R facilities and evaluating the potential benefits of introducing TODs in the network. However, before the proposed framework's recommendations can be used in practice, appropriate data must be collected, and all modeling choices and assumptions must be carefully considered.

Chapter 6 Conclusion

The objective of this study was to improve P&R services in metropolitan areas of Tennessee by optimal planning of the placement of these facilities. To produce quality results, demand and optimization models were integrated to incorporate the potential behavior of commuters when locating the facilities. Consequently, the potential use of TODs was examined in this network. A case study was conducted for the City of Nashville, and results were discussed. The results of the case study suggested that the optimal placement of P&R facilities had the potential to improve the network performance and reduce emission. In addition, in this particular case study, P&R facilities generally remained more favorable compared with TODs. Note that this does not imply that candidate locations for TODs may not be selected. Hence, further research is needed to identify ideal candidate locations for TODs.

One of the major challenges faced was the paucity of data in quantity and format needed. This specifically included the lack of access to existing survey data that captured the attitude of commuters in Tennessee, particularly Nashville, towards P&R services. To bypass this issue, an approach was developed to estimate the P&R demand model. The resulting demand model was then used within the optimization model. The validity of the developed integrated model was tested, and the numerical results suggested that the model was valid and could provide reasonable results, given the available data. Consequently, sensitivity analysis was conducted to evaluate the sensitivity of the results to the estimated parameters. The results showed that although the model was rather robust, the parameter choices could indeed impact the final recommendations of the model.

Hence, to ensure that the results of the framework provide actionable insights, it is recommended that additional steps be taken. First, appropriate data must be collected, possibly through surveys, that capture the attitude of commuters towards P&R facilities, compared with other alternatives. These data enable developing a reliable demand model that can predict the behavior of commuters towards different modes, including P&R facilities. Second, more precise 'travel time' and additional alternative specific attributes such as 'travel cost,' 'parking fare,' etc. may be needed to improve the prediction of the commuters' behavior in the demand model. Third, prediction performance of the demand model needs to be evaluated using a separate test data. In case of imbalanced data, balancing techniques must be leveraged to improve the prediction performance of the model across all modes. Fourth, appropriate candidate locations must be selected to be included in the model. Fifth, the objective function and model constraints must be clearly identified before executing the optimization model to obtain the recommendations. Lastly, feasible range of TOD characteristics must be clearly defined to enable a meaningful comparison between P&Rs and TODs and ensure actionable decisions regarding the placement of TODs in the network.

Reference

AASHTO. (2004). *Guide for Park-and-Ride Facilities.* . Washington, D.C.: American Association of State Highway and Transportation Officials.

AECOM. (2012). *STATE PARK-AND-RIDE GUIDE* Retrieved from https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/transit/documents/state-of-florida-park-and-ride-guide.pdf?sfvrsn=f947dc8_2

Aros-Vera, F., Marianov, V., & Mitchell, J. E. (2013). p-Hub approach for the optimal park-and-ride facility location problem. *European Journal of Operational Research, 226*(2), 277-285.

Arrington, G. B., & Cervero, R. (2008). *TCRP Report 128: Effects of TOD on Housing, Parking, and Travel*. Retrieved from TRB, Washington DC.

Ben-Akiva, M. E. (1973). *Structure of passenger travel demand models.* Massachusetts Institute of Technology.

Ben-Akiva, M. E., Steven R. Lerman, and Steven R. Lerman. (1985). Discrete choice analysis: theory and application to travel demand.

Bolger, D., Colquhoun, D., & Morrall, J. (1992). Planning and design of park-and-ride facilities for the Calgary light rail transit system. *Transportation research record, 1361*, 141.

Börsch-Supan, A. (1987). Econometric analysis of discrete choice. *Lecture notes in economics and mathematical systems, 296*, 202-211.

Burgess, J. J. S. (2008). *A comparative analysis of the Park-and-Ride/transit-oriented development tradeoff.* Massachusetts Institute of Technology.

Burns, E. (1979). Priority rating of potential park-and-ride sites. *ITE journal, 49*(2).

Cao, J., & Duncan, M. (2019). Associations among Distance, Quality, and Safety When Walking from a Park-and-Ride Facility to the Transit Station in the Twin Cities. *Journal of Planning Education and Research, 39*(4), 496-507.

Carlson, K., & Owen, A. (2019). Accessibility impacts of park-and-ride systems. *Transportation Research Record, 2673*(9), 72-82.

Cervero, R., Murphy, S., Ferrell, C., Goguts, N., Tsai, Y.-H., Arrington, G. B., Boroski, J., Smith-Heimer, J., Golem, R., Peninger, P., Nakajima, E., Chui, E., Dunphy, R., Myers, M., Mckay, S. and Witenstein, N. (2004). *TCRP Report 102: Transit-Oriented Development In The United States: Experiences,Challenges,And Prospects*. Retrieved from TRB, Washington DC.

Chen, X., & Kim, I. (2018). Modelling Rail-Based Park and Ride with Environmental Constraints in a Multimodal Transport Network. *Journal of Advanced Transportation, 2018*.

Chen, X., Liu, Z., Hua, D., & Kim, I. (2017). A new model for rail-based park-and-ride with feeder bus services. *Transportation research procedia, 21*, 79-86.

Cheng, L., Lai, X., Chen, X., Yang, S., De Vos, J., & Witlox, F. (2020). Applying an ensemble-based model to travel choice behavior in travel demand forecasting under uncertainties. *Transportation Letters, 12*(6), 375-385.

Cherrington, L. K., Brooks, J., Cardenas, J., Elgart, Z., Galicia, L. D., Hansen, T., Miller, K., Walk, M. J. (2017). *TCRP Research Report 192: Decision-Making Toolbox to Plan and Manage Park-and-Ride Facilities for Public Transportation*. Retrieved from TRB, Washington DC.

Cherrington, L. K., Brooks, J., Cardenas, J., Elgart, Z., Galicia, L. D., Hansen, T., Miller, K., Walk, M.J., Ryus, P., Semler, C., and Coffel, K. (2017). *TCRP Web only Document 69: Decision-Making*

Toolbox to Plan and Manage Park-and-Ride Facilities for Public Transportation: Research Report and Transit Agency Case Studies (2017). Retrieved from TRB, Washington DC.

City of Charlotte Chapter 15. Transit Oriented Development Districts (2019).

Coffel, K., Parks, J., Semler, C., Ryus, P., Sampson, D., Kachadoorian, C., Levinson, H.S., and Schofer, J. L. (2012). *TCRP Report 153: Guidelines for Providing Access to Public Transportation Stations*. Retrieved from TRB, Washington DC.

Cornejo, L., Perez, S., Cheu, R. L., & Hernandez, S. (2014). An approach to comprehensively evaluate potential park and ride facilities. *International Journal of Transportation Science and Technology, 3*(1), 1-18.

Donelson Transit-Oriented Redevelopment Plan (2018).

Du, B., & Wang, D. Z. (2014). Continuum modeling of park-and-ride services considering travel time reliability and heterogeneous commuters–A linear complementarity system approach. *Transportation Research Part E: Logistics and Transportation Review, 71*, 58-81.

Duncan, M. (2019). Would the replacement of park-and-ride facilities with transit-oriented development reduce vehicle kilometers traveled in an auto-oriented US region? *Transport policy, 81*, 293-301.

Duncan, M., & Christensen, R. K. (2013). An analysis of park-and-ride provision at light rail stations across the US. *Transport policy, 25*, 148-157.

Duncan, M., & Cook, D. (2014). Is the provision of park-and-ride facilities at light rail stations an effective approach to reducing vehicle kilometers traveled in a US context? *Transportation research part a: policy and practice, 66*, 65-74.

Evans, J. E. J., Pratt, R. H., Stryker, A., & Kuzmyak, J. R. (2007). *TCRP Report 95: Traveler Response To Transportation System Changes Chapter 17—Transit Oriented Development*. Retrieved from TRB, Washington DC.

Fan, W., Jiang, X., & Erdogan, S. (2016). *Land-use policy for transit station areas: park-and ride versus transit-oriented development.* Paper presented at the 95th annual meeting of transport research board.

Farhan, B., & Murray, A. T. (2008). Siting park-and-ride facilities using a multi-objective spatial optimization model. *Computers & Operations Research, 35*(2), 445-456.

Feldman, R., & Dagan, I. (1995). *Knowledge Discovery in Textual Databases (KDT).* Paper presented at the KDD.

Gayah, V. V., Stieffenhofer, K., & Shankar, V. (2014). *How can we maximize efficiency and increase person occupancy at overcrowded park and rides?*

Habib, K. N., Mahmoud, M. S., & Coleman, J. (2013). Effect of parking charges at transit stations on park-and-ride mode choice: lessons learned from stated preference survey in Greater Vancouver, Canada. *Transportation research record, 2351*(1), 163-170.

Haixiang, G., Yijing, L., Shang, J., Mingyun, G., Yuanyue, H., & Bing, G. (2017). Learning from class-imbalanced data: Review of methods and applications. *Expert Systems with Applications, 73*, 220-239. doi:10.1016/j.eswa.2016.12.035

Hamid, N. A., Mohamad, J., & Karim, M. R. (2007). *Parking duration of fringe Park-and-Ride users and delineation of stations catchment area: Case of the Kuala Lumpur conurbation.* Paper presented at the Proceedings of the Eastern Asia Society for Transportation Studies Vol. 6 (The 7th International Conference of Eastern Asia Society for Transportation Studies, 2007).

Haque, A. M., Brakewood, C., Rezaei, S., & Khojandi, A. (2021). A Literature Review on Park-and_Rides. *Journal of Transport and Land Use*. doi:10.5198/jtlu.2021.1923

Hart, W. E., Laird, C. D., Watson, J.-P., Woodruff, D. L., Hackebeil, G. A., Nicholson, B. L., & Siirola, J. D. (2017). *Pyomo-optimization modeling in python* (Vol. 67): Springer.

Hendricks, S., & Outwater, M. (1998). Demand forecasting model for park-and-ride lots in King County, Washington. *Transportation research record, 1623*(1), 80-87.

Hole, A. R. (2004). Forecasting the demand for an employee Park and Ride service using commuters' stated choices. *Transport Policy, 11*(4), 355-362.

Holguín-Veras, J., Reilly, J., Aros-Vera, F., Yushimito, W., & Isa, J. (2012). Park-and-ride facilities in New York City: economic analyses of alternative locations. *Transportation Research Record, 2276*(1), 123-130.

Holguın, J., Yushimito, W. F., Aros-Vera, F., & Reilly, J. J. (2012). User rationality and optimal park-and-ride location under potential demand maximization. *Transportation Research Part B: Methodological, 46*(8), 949-970.

Hou, B., Zhao, S., & Liu, H. (2020). A Combined Modal Split and Traffic Assignment Model With Capacity Constraints for Siting Remote Park-and-Ride Facilities. *IEEE Access, 8*, 80502-80517.

Islam, S. T., Liu, Z., & Sarvi, M. (2015). *Park-and-Ride network design in a bi-modal transport network optimising network reliability.* Paper presented at the Proc., Australasian Transport Research Forum (ATRF), Sydney, New South Wales, Australia.

Karamychev, V., & van Reeven, P. (2011). Park-and-ride: Good for the city, good for the region? *Regional Science and Urban Economics, 41*(5), 455-464.

Kimpton, A., Pojani, D., Sipe, N., & Corcoran, J. (2020). Parking behavior: Park 'n'ride (PnR) to encourage multimodalism in Brisbane. *Land Use Policy, 91*, 104304.

King, G., & Zeng, L. (2003). Logistic regression in rare events data. *Journal of Statistical Software, 8*, 137-163. doi:10.18637/jss.v008.i02

Koppelman, F. S., & Bhat, C. (2006). A Self Instructing Course in Mode Choice Modeling : Multinomial and Nested Logit Models by with technical support from Table of Contents. *Elements, 28*, 501-512. doi:10.1002/stem.294

Kotsiantis, S., Kanellopoulos, D., & Pintelas, P. (2006). Handling imbalanced datasets: A review. *GESTS International Transactions on Computer Science and Engineering, 30*(1), 25-36.

Lam, W. H., Holyoak, N. M., & Lo, H. (2001). How park-and-ride schemes can be successful in Eastern Asia. *Journal of urban planning and development, 127*(2), 63-78.

Li, J.-Q., Zhou, K., Zhang, L., & Zhang, W.-B. (2010). *A multimodal trip planning system incorporating the park-and-ride mode and real-time traffic/transit information.* Paper presented at the Proceedings ITS World Congress.

Liu, Z., Chen, X., Meng, Q., & Kim, I. (2018). Remote park-and-ride network equilibrium model and its applications. *Transportation Research Part B: Methodological, 117*, 37-62.

Lu, X.-S., & Guo, R.-Y. (2015). A bi-objective model for siting park-and-ride facilities with spatial equity constraints. *Promet-Traffic and Transportation, 27*(4), 301-308.

MARTA. (2010). *MARTA Transit-Oriented Development Guidelines*.

Martin, P. C., & Hurrell, W. E. (2012). Station parking and transit-oriented design: transit perspective. *Transportation Research Record, 2276*(1), 110-115.

Mock, A., & Thill, J.-C. (2015). Placement of rapid transit park-and-ride facilities. *Transportation Research Record, 2534*(1), 109-115.

Niles, J. S., & Pogodzinski, J. (2016). *Bus Transit Operational Efficiency Resulting from Passenger Boardings at Park-and-Ride Facilities*.

Palakurthy, R., Tung, L.-W., Cryer, L., & Bell, L. (2017). Trip Generation Rates at Park-and-Ride Facilities with Regional Bus and Light Rail Service: A Supplement to ITE Trip Generation Data. *Transportation Research Record, 2651*(1), 60-70.

Pang, H., & Khani, A. (2018). Modeling park-and-ride location choice of heterogeneous commuters. *Transportation, 45*(1), 71-87.

Péladeau, N. (2004). QDA miner qualitative data analysis software, user's guide. *Montreal: Provalis Research*.

Rajman, M., & Vesely, M. (2004). From text to knowledge: Document processing and visualization: A text mining approach. In *Text mining and its applications* (pp. 7-24): Springer.

Rezaei, S., Khojandi, A., Haque, A. M., Brakewood, C., M, J., & Cherry, C. (2021). Performance Evaluation of Mode Choice Models Under Balanced and Imbalanced Data Assumptions. *Transportation Letters: the International Journal of Transportation Research*, DOI: 10.1080/19427867.2021.1955567.

Sargious, M. A., & Janarthanan, N. (1983). Forecasting demand for the park-and-ride mode and determining the optimal location of stations. *Canadian Journal of Civil Engineering, 10*, 695-702. doi:10.1139/l83-098

Sharma, B., Hickman, M., & Nassir, N. (2019). Park-and-ride lot choice model using random utility maximization and random regret minimization. *Transportation, 46*(1), 217-232.

Song, Z. (2013). Transition to a transit city: case of Beijing. *Transportation research record, 2394*(1), 38-44.

Song, Z., He, Y., & Zhang, L. (2017). Integrated planning of park-and-ride facilities and transit service. *Transportation Research Part C: Emerging Technologies, 74*, 182-195.

Stieffenhofer, K. E., Barton, M., & Gayah V, V. (2016). Assessing park-and-ride efficiency and user reactions to parking management strategies. *Journal of Public Transportation, 19*(4), 5.

Train, K. E. (2003). Discrete choice methods with simulation. *Discrete Choice Methods with Simulation, 9780521816*, 1-334. doi:10.1017/CBO9780511753930

Truong, L. C., & Marshall, W. E. (2014). Are park-and-rides saving the environment or just saving parking costs? Case study of Denver, Colorado, light rail system. *Transportation Research Record, 2419*(1), 109-117.

Turnbull, K. F., Pratt, R. H., Evans, J. E. J., & Levinson, H. S. (2004). *TCRP REPORT 95 Traveler Response to Transportation System Changes Chapter 3—Park-and-Ride/Pool*. Retrieved from Washington DC.

VDOT. (2018). *Park and Ride Design Guidelines*. Retrieved from https://www.virginiadot.org/travel/resources/parkAndRide/Park_Ride_Design_Guidelines.pdf

Wang, F., & Ross, C. L. (2018). Machine Learning Travel Mode Choices: Comparing the Performance of an Extreme Gradient Boosting Model with a Multinomial Logit Model. *Transportation research record, 2672*, 35-45. doi:10.1177/0361198118773556

Wang, H., Meng, Q., & Zhang, X.-N. (2014). Park-and-ride network equilibrium with heterogeneous commuters and parking space constraint. *Transportation Research Record, 2466*(1), 87-97.

Wang, H., Meng, Q., & Zhang, X.-N. (2015). Optimal parking pricing in many-to-one park-and-ride network with parking space constraints. *Transportation Research Record, 2498*(1), 99-108.

Wang, J. Y., Yang, H., & Lindsey, R. (2004). Locating and pricing park-and-ride facilities in a linear monocentric city with deterministic mode choice. *Transportation Research Part B: Methodological, 38*(8), 709-731.

Webb, A., & Khani, A. (2020a). Park-and-Ride Choice Behavior in a Multimodal Network with Overlapping Routes. *Transportation research record, 2674*, 150-160. doi:10.1177/0361198120908866

Webb, A., & Khani, A. (2020b). Park-and-Ride Choice Behavior in a Multimodal Network with Overlapping Routes. *Journal of Transportation Research Record*, 0361198120908866.

WeGo Public Transit. (2020). *WeGo Park and Ride Strategic Investment Plan*. Retrieved from

WordStat 7 User's Guide. (2014). *Montreal: Provalis Research*.

Zhang, D. (2014). *Spatial distribution of park-and-ride demand.* University of Delaware,

Zhao, X., Chen, P., Jiao, J., Chen, X., & Bischak, C. (2019). How does ‘park and ride’perform? An evaluation using longitudinal data. *Transport policy, 74*, 15-23.