Campus Parking Supply Impacts on Transportation Mode-Choice

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Abstract

Parking demand is a significant land-use problem in campus planning. The parking policies of universities and large corporations with facilities located in small urban areas shape the character of their campuses. These facilities will benefit from a simplified methodology to study the effects of parking availability on transportation mode mix and impacts on recruitment and staffing policies. This study introduces an analytical framework using simple models to provide campus planners with insights about how parking supply and demand affects campus transportation mode choice. The methodology relies only on aggregate mode choice data for the special generator zone and the average aggregate volume/capacity ratio projections for all external routes that access the zone. This reduced data requirement significantly lowers the analysis cost and time and obviates the need for specialized modelling software and spatial network analysis tools. Results illustrate that the framework is effective for analysing mode choice changes under different scenarios of parking supply and population growth.

Keywords: transportation mode choice, parking, demand modelling, land-use planning, university campus, special generator

Subject classification codes: Traffic and Transport Planning

Introduction

Land use planners benefit from understanding how parking capacity affects organizational goals and decision-making. Universities and other large employers rely on facility planners to build adequate parking capacity to support recruitment and staffing policies. As a special trip generator, universities must consider the degree to which a chronic lack of parking could have unintended consequences such as limiting the pool of students, faculty, and staff willing to relocate to a rural or small urban area. Families that strongly favour campuses with many off-campus housing options are likely to limit their choices to 'automobile friendly' campuses. Similarly, large employers with trip generation and attraction similar to universities must consider the degree to which parking availability is a factor in attracting employees to a rural or small urban area.

The North Dakota State University (NDSU), one of the largest employers in the small urban Fargo-Moorhead (F-M) metropolitan area, serves as a case study. Data from the NDSU Office of the Registrar shows that enrolment has been growing at an annual average rate of about 4% (NDSU 2010) as shown in Figure 1.

Figure 1. NDSU annual enrolment and average growth rate

The enrolment growth rate is a function of specific university policies and recruitment target markets. Planners should be aware that with each new academic year, changes in the campus enrolment and population mode biases might be due in part to parking policy changes in previous years, resulting in a dynamic cycle of cause-and-effect that a simple model won't necessarily predict. This study will simplify the scenarios by maintaining a constant average population growth rate to focus the analysis on providing insights into the interactions between

parking supply and transportation mode choice.

The parking problem

The number of permits issued for NDSU campus parking had exceeded the number of parking stalls available by 67% in the survey year of 2002 (Peterson *et al.* 2005). Despite growing enrolment, parking supply remained nearly constant at about 8,159 stalls. Campus construction projects often temporarily remove a significant number of these stalls, thus exacerbating the parking demand. The NDSU survey found that a majority of students (84%) were unsatisfied with parking availability and affordability. With constant parking supply, demand will continue to increase proportionally with additional permit sales. If this continues drivers will begin to spend more time searching for parking, wasting fuel, and increasing their travel cost. Time spent searching for parking also decreases productivity and increases greenhouse-gas emissions.

According to the most recent survey published for the NDSU campus more than 90% of the respondents owned cars (Ripplinger *et al*. 2009). About 53% used automobiles most commonly for trips between campus and home or other activities. Roughly half the population lived within one mile of campus and the remainder lived within five miles. The average survey respondent reportedly walked or cycled when travelling within one mile, took the bus when travelling within two miles, and used automobile, carpool, or motorcycle for greater distances. About 32% of the population most commonly utilized non-motorized means of transport, 12% cycled and 20% walked. Although the university provides a free circulator bus service, only 7% of off-campus residents utilized it as their most common mode when travelling between campus and their residence. Four percent most commonly used carpool and four percent most commonly used motorcycles. These statistics indicate that the aggregate NDSU population at the time had a

strong preference for driving alone. As the parking problem worsens with the population growth, the mode-mix choices will likely change.

Goals and objectives

The main goal of this study is to determine how changes in parking demand will affect campus transportation mode-mix as population grows. A United States of America transit study found that 65% of its higher education campuses are located in suburban, small urban, semi-rural, and rural settings while the rest (35%) are located in urban environments (TCRP 2008). Campus planners can use the analytical framework as a low-cost tool to evaluate decision-making scenarios and policy objectives for parking on campus. Decision-makers should be aware that theoretical analysis and mathematical models attempt to describe the overall statistical behaviour of an aggregate population, and not necessarily individuals. Consequently, scenarios will contain inherent uncertainties.

This framework is designed to support follow-up analysis of the impacts of real-time information technology on various mode choice attributes. A future study will investigate how emerging parking spot finder technologies could affect mode choice relative to this baseline case study. In addition to the parking demand factor (PKD), the analysis limits mode choice attributes to those that most significantly affect travel time and cost, namely in-vehicle-travel-time (IVTT) and out-of-vehicle-travel-time (OVTT). To further limit the analysis scope, the model accounts for factors such as convenience, weather, income, and safety as mode specific bias parameters.

The study objectives are to:

(1) Develop an analytical framework suitable for analysing an intra-zonal transportation related problem or opportunity

(2) Minimize the amount of data (expense) needed to build and calibrate the model

(3) Develop a mode choice model that utilizes aggregate survey results

(4) Remove the need for expensive Geographic Information System (GIS) tools to produce network skims of all zones within the travel region

(5) Build a model that does not require substantial computing resources and specialized (expensive) modelling software

(6) Support a variety of scenarios such as

    (a) changes in parking spot capacity and their schedule of availability

    (b) changes in average travel distance due to urban population growth and population centre shifting

    (c) changes in transit supply and schedule reliability

The framework combines mathematical techniques with software programming to achieve these goals and objectives.

Literature review

Large urban campuses located in or at the periphery of the central business district (CBD) typically experience severe parking problems (Brown-West 1996). Early studies of driving on campus determined that increased automobile ownership levels among students and faculty/staff has led to severe parking demands on many university campuses (Pendakur 1968). However, almost no studies have since reported on how parking demand affects changes in transportation mode choice with population growth. A University of Wisconsin-Madison study examined

parking lot choice relative to parking prices and walking distances (Harmatuck 2007). The study found that choice was more elastic with price than with distance but did not examine the propensity for mode mix shifting. A case study comparing the Louisiana State University auto restricted zone policy (ARZ) with parking permit price changes found that ARZ was a more significant factor in lowering demand for parking permits than price increases were (Stuart and Sarangi 2011). The study also determined that while driving was a primary mode choice, students were willing to adopt other modes if their facilities are improved.

Several studies found a general bias towards certain modes of transportation. A survey of the NDSU population found that *convenience* was the leading factor in automobile mode choice for more than 90% of the surveyed respondents (Peterson *et al.* 2005). The study covered three different campuses in the F-M metropolitan area and found consistently that well over 90% of the student, staff, and faculty population in the region rely on their personal automobiles for commuting. About one-half of the students lived within two miles of campus. All three campuses provide a free circulator service. In general, most large university campuses provide transit services. A Transit Cooperative Research Program (TCRP) synthesis (2008) found that more than 90% of campuses in the United States had access to a fixed route bus service. Most of the NDSU respondents were generally aware of the major benefits of choosing transit over automobile, including cost savings, reducing traffic congestion, reducing parking demand, and environmental stewardship.

Studies find that a university campus population will be generally biased towards motorized or non-motorized modes of transportation, and that parking costs and availability will have a positive effect on non-motorized modes such as cycling or walking (Miller and Handy 2012). The direction of bias depends on the degree of urbanization, availability of modal

facilities, and climate. For example, a University of California Davis study reported a strong bias towards cycling because of its well-developed bicycle infrastructure and average low winter temperature above 36 degrees (Bleechmore *et al.* 2011). However, a University of North Dakota (UND) study reported a strong bias towards personal automobiles, which could be in part due to low levels of congestion in the region as well as an average winter temperature that is well below freezing (Scott *et al.* 2011).

Given the high automobile ownership level among the university campus demographic and a lack of land within walking distance to build new parking facilities, some universities have adopted policies that prohibit driving on campus. About 43% of the universities surveyed prohibit vehicles on campus (Wecker 2011). Among universities that allow automobiles, the top 16 reported that more than 90% of the students currently drive to campus. In the NDSU study, this driving bias also extends to the external zones of the entire metropolitan area which sustained a relatively consistent population growth rate of 1.7% annually since 1980 (FM-COG 2012). Transit became free of charge to students from the area's four major colleges/universities in 2001, and transit agencies observed a 5.7-fold increase in ridership since then.

Analysis methodology

Planners using mathematical models must be aware that if the population demographic changes at anytime, then the present state of the system could also change in terms of its mode choice bias, mode choice parameter attributes, and available choice set. Therefore, planners must re-calibrate models periodically to account for changes in the population characteristics. For example, with a shortage of on-campus housing, the new enrolment demographics may prefer off-campus housing, resulting in an increase in parking demand. Without information about how the demographic changes each academic year, the model will maintain the base-year choice

elasticities to forecast mode-mix shifting with population growth.

Evaluation of current system state

According to the NDSU survey, one-third fewer students reported having parking permits than the previous year. This reduction hints at the direction of automobile mode choice elasticity with increasing parking demand. Walking and cycling appeared to be attractive options for a significant percentage of the base-year population. However, with future crowding and increased walk or cycle time, one hypothesis is that this choice could eventually decline, particularly in the winter months.

Travel model synthesis

This analytical framework utilizes a modified urban transportation modelling systems (UTMS) approach that includes iterations of four main procedures. These are (1) trip generation, (2) trip distribution, (3) modal choice, and (4) network assignment (Ortuzar and Willumsen 2002). The first two procedures depend on university enrolment and staffing policies. The last two depend on attributes of the campus and the surrounding metropolitan area transportation facilities. The approach for this framework refers to the last step as cost assignment because it aggregates the details of network assignment to reduce data collection and analysis software requirements.

Figure 2. Parking demand model configuration

The model has two loops as shown in Figure 2. The first loop increments the analysis year and population while the second implements model iteration to converge when travel cost reaches an equilibrium condition. The model updates an aggregate travel cost by mode each year based on changes to the mean modal trip length and congestion delays from increasing traffic volume. It

converges to an equilibrium trip distribution after iterating between cycles of distribution, mode choice, and cost assignment. The sections that follow describe the data and modifications to the four model steps.

Data collection

In a typical travel demand study, planners divide the demographic area into multiple transportation analysis zones (TAZ) and then estimate and calibrate models to predict the traffic volumes between them. The multi-zonal approach requires a substantial amount of data collection, GIS coding that includes the aggregate socio-demographic characteristics for each TAZ, and verification of network attributes for facilities throughout the area. This data collection process is very time consuming and expensive. Fundamentally, models based on TAZs cannot accurately describe activities within the zones, and hence would be sub-optimal for analysing an intra-zonal parking issue.

For this particular type of analysis, it is far less important to know specifically where the trips go and return from than it is to know the average distance travelled from the zone in each transport mode. A trip length frequency distribution (TLFD) by mode provides the average distance by computing the expected value of their respective distributions. The average radial distance travelled from campus provides the travel time and impedance attributes that most significantly affect mode choice. Hence, this trip distribution model estimates the average radial distance from campus that individuals travel by each selected transportation mode, irrespective of the external zone producing or attracting the trip. This average distance will tend to shift further away from campus as the surrounding area population density increases, and when off-campus dwellers begin to seek lower cost housing further away. This phenomenon is

characteristic of urban sprawling where a population centre shifts with increasing density (USDOC 2010).

Trip generation

The NDSU population grows with enrolment such that,

$$PP_{NDSU(y)} = PP_{NDSU(y-1)}(1 + \gamma_{NDSU}) \tag{1}$$

where γ_{NDSU} is the projected campus population growth rate, and y is an annual time step. Throughout this analysis, the notation used for the loop iterations is a subscript with the iteration year in parenthesis. The following function estimates the number of trips generated for population P_{area} such that,

$$T_G(P_{area}) = P_{area} \times [T_{auto} + T_{bus} + T_{carpool} + T_{motorcycle} + T_{non-motorized}] \tag{2}$$

where T_{auto}, T_{bus}, $T_{carpool}$, $T_{motorcycle}$, and $T_{non-motorized}$ are the annual average daily trip rates for users of automobile, bus, carpool, motorcycle, and non-motorized modes of transportation respectively. The model combines walking and cycling into a single non-motorized category because bicyclists tend to share walking paths and avoid the main motorized traffic streams. This model generates the base year trips as,

$$Trips_{NDSU(0)} = T_G(PP_{NDSU(0)}) \tag{3}$$

and incremental trips for the next year as,

$$\Delta Trips_{NDSU(y)} = T_G(PP_{NDSU(y-1)} \times \gamma_{NDSU}) \tag{4}$$

to yield total trip volume for the analysis year as,

$$Trips_{NDSU(y)} = Trips_{NDSU(y-1)} + \Delta Trips_{NDSU(y)} \tag{5}$$

The annual average trip frequency is,

$$T_{freq(j)} = \sum_{k=1}^{6} \phi_k k \tag{6}$$

where sub-population share ϕ_k generates k trips using mode j. The rate of trip production by mode is the product of the population proportion using that mode and the trip frequency such that,

$$T_{j(y)} = P_{j(y)} \times T_{freq(j)} \tag{7}$$

where $P_{j(y)}$ is the population proportion using mode j and generating $T_{j(y)}$ trips in the yth horizon year. For example, the trip generation rate for automobile users is,

$$T_{auto(y)} = P_{auto(y)} \times T_{freq(auto)} \tag{8}$$

Model calibration requires the average trip rate by mode. The NDSU case study suggests that $T_{NDSU} = T_{freq(j)}$ for all modes j where T_{freq} is the aggregate population trip frequency.

The trip generation model grows the non-NDSU population in the F-M area (the differential F-M population) such that,

$$PP_{FM(y)} = PP_{FM(y-1)}(1 + \gamma_{FM}) \tag{9}$$

where the F-M metropolitan area growth rate is γ_{FM} and the number of trips generated is,

$$Trips_{FM(y)} = PP_{FM(y-1)}T_{FM} \qquad (10)$$

with T_{FM} being the differential F-M population aggregate trip frequency.

Trip distribution

This model distributes trips by radial distance from campus. It first converts person trips to vehicle trips to estimate the traffic volume to and from campus. Secondly, it adds this traffic volume to the F-M area traffic volume to update the travel impedance in the cost assignment application. Thirdly, it adjusts the average travel distance by mode as a function of population volume changes to simulate urban sprawling.

Vehicle volumes. For ride-alone scenarios the automobile annual average daily traffic (AADT) volume is,

$$V_{auto(y)} = Trips_{auto(y)} / T_{freq} \qquad (11)$$

and the motorcycle AADT is,

$$V_{mc(y)} = Trips_{mc(y)} / T_{freq} \qquad (12)$$

These units must match in terms of average daily travel (ADT) or average annual daily travel (AADT) statistics. The former is the average 24-hour person trip volume for some period less than one year, typically one month or a season, and the latter is the total annual trips divided by 365 days (Roess *et al.* 2011). The number of buses and carpools will be based on their average vehicle passenger capacity. The AADT of bus vehicle volume is,

$$V_{bus(y)} = \left\lceil \frac{P_{bus(y)} T_{freq}}{C_{bus}} \right\rceil^{ceil} \tag{13}$$

where $P_{bus(y)}$ is the population proportion travelling by bus in that analysis year. The average bus capacity for the iteration period is C_{bus}. This ceiling function stipulates that the agency will adapt the bus supply to meet demand. The model can simulate various bus supply rates by incorporating the associated headways and average delay into the OVTT and IVTT parameters.

The AADT carpool volume is,

$$V_{cp(y)} = \left\lceil \frac{P_{cp(y)} T_{freq}}{C_{cp}} \right\rceil^{ceil} \tag{14}$$

where the average carpool occupancy for the analysis year is V_{cp}. The model converts the vehicle volume mix into passenger car equivalents (PCE) using typical equivalency factors such that,

$$V_{PCE(y)} = V_{auto(y)} + V_{cp(y)} + V_{bus(y)} PCE_{bus(y)} + V_{mc(y)} PCE_{mc(y)} \tag{15}$$

Setting the vehicle volume that the campus produces and attracts to be equal gives the vehicle volume contributions from campus as,

$$V_{NDSU(y)} = 2 \times V_{PCE(y)} \tag{16}$$

The external-external (EE) trips relative to the special generator will affect travel times for those trips that leave the zone. Therefore, this analysis can justifiably aggregate those EE trips and account for them separately from trips leaving and entering the special generator zone, that is, the external-internal (EI) trips.

The non-campus portion of AADT vehicle volume for the Fargo-Moorhead (F-M) metropolitan area is proportional to the aggregate population trip rate such that,

$$V_{FM(y)} = \frac{PP_{FM(y)}}{T_{FM}}$$ (17)

where the daily PCE vehicle trip rate T_{FM} includes EE trips through the metropolitan area. These are typically trucks traversing trade routes. The model accounts for those and other types of vehicles by adding them as a proportion of the passenger car volume, typically 10%. Hence, the total vehicle volume in the area is,

$$V_{area(y)} = V_{FM(y)} + V_{NDSU(y)}$$ (18)

Radial distance shift. The traditional *gravity model* estimates the vehicle volume moving between zones from their trip production and attraction volumes and the friction or cost factors between zones. Such an analysis requires data in excess of that which is desirable for characterizing the intra-zonal situation. Hence, this framework uses instead the radial trip length frequency distribution (TLFD) from campus to provide average travel impedance factors for each mode. This approach obviates the need for an expensive and time-consuming data collection process to describe the network facilities for zones external to the analysis area. Figure 3a shows the TLFD from the NDSU survey. The data suggests that respondents walked or cycled for trips less than half-mile and used a motorized mode for trips greater than one mile.

A friction factor model for the non-motorized mode appears to fit a "gamma-distribution" best such that,

$$FF_{nm(y)}(d) = A_{nm}d^{-\beta_{nm}}e^{-\gamma_{nm}d}$$ (19)

The calibration parameters are A_{nm}, β_{nm}, and γ_{nm} and d is distance. The travel distance distribution for bus and automobile modes appear to fit a Weibull distribution (Nelson 1982) such that,

$$FF_{bus(y)}(d) = A_{bus}\left(\frac{k_{bus}}{\lambda_{bus}}\right)\left(\frac{d}{\lambda_{bus}}\right)^{k_{bus}-1} e^{-\left(d/\lambda_{bus}\right)^{k_{bus}}} \tag{20}$$

where A_{bus}, k_{bus}, and λ_{bus} are amplitude, shape, and scale calibration parameters respectively. The distribution for automobiles, carpools, and motorcycles is similar but with calibration parameters A_{auto}, k_{auto}, and λ_{auto}. Figure 3b shows the results of a model calibrated with the NDSU survey data. The expected value of each of these distributions yields the average travel distance by mode j such that,

$$D_{avg(y)} = \int_0^{D_{max}} x FF_{j(y)}(x)dx \tag{21}$$

where $f(x)$ is the trip length frequency distribution function with x as the distance variable.

Figure 3. (a) Trip length distribution, and (b) joint distribution model

The average travel distance by mode will tend to shift with population growth and density. The model simulates a simple non-linear population-spread that produces an average distance shift from campus as a function of relative population density. This component of the model changes the average distance travelled by mode, which updates the IVTT. Changes in IVTT and OVTT affect mode choice based on their respective elasticities. The resulting change in modal mix will in turn update the trip production rates for each mode in the next model iteration cycle. The

change in trip volume by mode will determine the vehicle volume for the zone, which will again affect IVTT. The model will iterate until it converges to an equilibrium state of mode-mix and minimum travel time (cost) for the entire system.

As the campus population grows, so will the likely number of trips and their average distance distribution from campus. The distance shift factor is the amount that the average radial distance from campus increases for each mode, as a function of the proportional trip volume change relative to the base year. A simple estimate for the distance shift model is,

$$PP_{shift(j)} = \beta_{shift(j)} \ln(PP_{ratio(j)}) + 1 \qquad (22)$$

where $PP_{shift(j)}$ is the distance shift factor of the mean travel distance for mode j, $PP_{ratio(j)}$ is the ratio of mode j vehicle volume as a proportion of the base year volume, and $\beta_{shift(j)}$ is the calibration parameter for that mode. For clarity, Figure 4 illustrates population shift factors for two mode shift parameters.

Figure 4. Comparison of population shift factors

This example shows that when the vehicle volume quadruples, the average travel distance from campus will increase by about 40% for a mode with calibration factor $\beta = 0.3$, and about 30% for a mode with calibration factor $\beta = 0.2$. Given the rural and small urban setting, the population shift factor for this analysis period is negligible.

Modal split

The mode choice model uses a multinomial *logit* estimation based on utility functions that contain the IVTT, OVTT, and PKD attributes previously described.

Utility function. In theory, the rational decision maker maximizes a utility function $U_{gj} = V_{gj} + \varepsilon_{gj}$ that forms the basis for the traveller's decision. U_{gj} is the random utility of alternative j for group g, where V_{gj} is the systematic or observable portion of the function. The random portion of the function is ε_{gj} and accounts for the fact that the group will choose the alternative that on average maximizes their utility. Planners should be aware that the group might not necessarily choose the rational alternative that maximizes utility because this is a statistical construction. The systematic portion of the utility is a function of the attributes of the alternatives and the characteristics of the group selecting them. For this analysis, the estimated utility function for automobile choice is,

$$V_{auto} = \alpha_{0(auto)} + \alpha_{1(auto)} X_{1(auto)} + \alpha_{2(auto)} X_{2(auto)} + \alpha_{3(auto)} X_{3(auto)} \tag{23}$$

for bus it is,

$$V_{bus} = \alpha_{0(bus)} + \alpha_{1(bus)} X_{1(bus)} + \alpha_{2(bus)} X_{2(bus)} + \alpha_{3(bus)} X_{3(bus)} \tag{24}$$

for carpool (cp) it is,

$$V_{cp} = \alpha_{0(cp)} + \alpha_{1(cp)} X_{1(cp)} + \alpha_{2(cp)} X_{2(cp)} + \alpha_{3(cp)} X_{3(cp)} \tag{25}$$

for motorcycle (mc) it is,

$$V_{mc} = \alpha_{0(mc)} + \alpha_{1(mc)} X_{1(mc)} + \alpha_{2(mc)} X_{2(mc)} + \alpha_{3(mc)} X_{3(mc)} \tag{26}$$

and for non-motorized (nm) modes it is,

$$V_{nm} = \alpha_{0(nm)} + \alpha_{1(nm)} X_{1(nm)} + \alpha_{2(nm)} X_{2(nm)} + \alpha_{3(nm)} X_{3(nm)} \tag{27}$$

A maximum likelihood approach estimates the parameters $\alpha_{n(j)}$ for all five modes based on the observed aggregate mode choice and the average values for their respective attributes. Choice theory postulates that the probability that a given mode alternative j from the choice set C_g available to group g will be the maximum utility alternative and hence chosen. This probability is, $P_{gj} = P(U_{gj} \geq U_{gi}) \; \forall j \in C_g$. Substituting, $U_{gj} = V_{gj} + \varepsilon_{gj}$ gives,

$$P_g(j|C_g) = P\left(\varepsilon_{gj} - \varepsilon_{gi} \leq V_{gi} - V_{gj}, \forall_j \in C_g\right) \tag{28}$$

which is the joint cumulative distribution function of the random variable $(\varepsilon_{gj} - \varepsilon_{gi})$ evaluated at the points $(V_{gi} - V_{gj})$. The solution requires a known distribution of the random variables. The probability evaluates to the *probit* model when the ε's are distributed multinomially normal. However, the multinomial *probit* is not analytically closed form. A traditional work around is to assume a Gumbel Type I distribution instead where the ε's are independently and identically distributed (iid) across alternatives (Hensher and Johnson 1981). This produces the following more mathematically convenient multinomial *logit* model,

$$P_j = \frac{e^{V_j}}{\sum\limits_{\forall j} e^{V_j}}, j \in C_g \tag{29}$$

This model describes the probability of mode choice j as the ratio of the utility exponent for that mode to the sum of utility exponents for all modes.

Explanatory variables. Mode choice studies for university campuses consistently find that respondents rank convenience highest among factors leading to their choice (Scott *et al.* 2011). Intuitively, climatic conditions typically increase the disutility of OVTT while distance and

congestion levels place a heavy disutility on IVTT. The model estimates non-explicit factors such as convenience, weather, income, and safety as mode bias parameters. This is justifiable because mode bias tends to be a strong function of household type, typical weather conditions during the semester, income, gender, and ethnicity (Mahlawat *et al*. 2007). This utility model assigns $X_1 = $ IVTT, $X_2 = $ OVTT, and $X_3 = $ PKD with their corresponding coefficients α_{1j}, α_{2j}, and α_{3j} for each of the five modes with $j \in \{1, 2, 3, 4, 5\}$. The constant $\alpha_{0(j)}$ represents an alternative specific bias for mode j.

Parameter estimation. The calibration process produces coefficient estimates by constructing a *posterior* probability that maximizes the likelihood that the model generated the observed aggregate choices and attribute values. The maximum likelihood solution requires a joint probability density function of the mode choices that maximizes the log of that function, also known as the log-likelihood function (Ben-Akiva and Lerman 1995). The joint probability density function is,

$$L(\hat{\alpha}_{k(j)}) = \prod_{\forall j} P_j(\hat{\alpha}_{k(j)}) \tag{30}$$

and the log-likelihood function is,

$$LL(\hat{\alpha}_{k(j)}) = \sum_{\forall j} \ln P_j(\hat{\alpha}_{k(j)}) \tag{31}$$

Taking the first derivative of the log-likelihood function, equating it to zero, and solving for the $\hat{\alpha}_{kj}$ parameters produces an estimate of the values that maximizes the function.

Mode choice elasticity. The direct elasticity of the probability of choosing mode j with respect to

the utility attribute is (Ben-Akiva and Lerman 1995),

$$\eta_{X_{k(j)}}^{Pj} = \left[1 - P_j\right]\left(X_{k(j)}\right)\alpha_{k(j)} \tag{32}$$

For example, the elasticity of choosing bus with respect to the attribute PKR is,

$$\eta_{PKR}^{Bus} = \left[1 - P_{Bus}\right]\left(PKR\right)\alpha_{3(bus)} \tag{33}$$

Elasticities provide a uniform basis for comparing choice tendencies with the same degree of change for each attribute.

Trip cost

Factors that affect mode choice are both internal and external to the zone. Parking supply, crowding on campus, the average walking distance to a bus stop, and bus schedule reliability are all internal factors. Traffic congestion outside the zone will affect IVTT for both automobiles and buses travelling to and from the special generator zone. Trip generation and attraction rates will be proportional to the campus population size. External zone congestion will be proportional to the combined campus and metropolitan area vehicle volumes. To reduce the cost of analysis, this framework relies only on the fact that travel time through the average radial distance from campus will settle to an equilibrium condition that produces an average travel time for each mode that equalizes the trip impedance for all travellers.

The annual average daily in-vehicle travel time (IVTT) for all automobiles and motorcycles is a function of the AADT volume for the access routes to and from the special generator zone. Based on the Bureau of Public Roads (BPR) formula for travel time (TRB 2010),

$$IVTT_{auto(y)}^{[n]} = \frac{D_{avg\_auto(y)}}{S_{avg\_autoFF(y)}} \left[1 + \tau_{auto} \left(\frac{V_{area(y)}}{C_{area(y)}} \right)^4 \right] \qquad (34)$$

where $IVTT_{auto(y)}^{[n]}$ is the in-vehicle travel time for automobiles in analysis year y and model

iteration n. The model iterates to distribute the AADT volume $V_{area(y)}$ based on the present IVTT

cost.

For the horizon year y, $C_{area(y)}$ is the average traffic capacity for all access routes to and

from campus, $D_{avg\_auto(y)}$ is the average travel distance for automobile trips, $S_{avg\_autoFF(y)}$ is the

average automobile speed through the average radial distance from campus in non-interfering

flow conditions, and τ_{auto} is the BPR formula parameter with a typical calibration value of 0.15.

The average automobile speed includes non-interfering flows through both interrupted and

uninterrupted segments, and hence includes time for intersection and traffic lights stops. The

model maintains the same signal timing and free-flow conditions throughout the analytical

period.

The value for $C_{area(y)}$ requires knowledge of the annual average daily V/C and vehicle

volume $V_{area(y)}$ for all routes that travellers use to and from campus such that,

$$C_{area(y)} = V_{area(y)} \left(\frac{V}{C} \right)_{(y)} \qquad (35)$$

The (Peterson *et al*. 2005) study provides calibration data for the initial average travel distance

$D_{avg\_auto(0)}$ and initial average travel speed $S_{avg\_autoFF(0)}$ for the base year trip distribution.

The average travel time for buses is,

$$IVTT_{bus(y)}^{[n]} = T_{avg\_bus(y)} \left[1 + \tau_{bus} \left(\frac{V_{area(y)}}{C_{area(y)}} \right)^4 \right] \tag{36}$$

where $T_{avg\_bus(y)}$ is the average travel time for bus under non-interfering traffic conditions and includes the time for passenger boarding and alighting. This model equates the τ_{bus} calibration parameter to that of automobiles. The model also postulates that the transit agency will attempt to maintain the same bus schedule by adapting transit supply to meet new demands. This is an important consideration because without additional transit supply to compensate for travel delays, the average headway will increase with area congestion levels. This will in turn increase the average bus wait time, which is a component of the out-of-vehicle travel time (OVTT) where,

$$OVTT_{bus(y)}^{[n]} = T_{avg\_bus\_wait(y)} + OVTT_{nm(y)}^{[n]} \tag{37}$$

The OVTT for non-motorized modes will be the total average walking and cycling travel times. The model estimates non-motorized travel times as a function of crowding and sidewalk capacity on campus such that,

$$OVTT_{nm(y)}^{[n]} = T_{avg\_nmFF(y)} \left[1 + \tau_{nm} \left(\frac{V_{nm(y)}}{C_{nm(y)}} \right)^{\lambda} \right] \tag{38}$$

where $V_{nm(y)}$ is the average path volume for non-motorized modes on campus, which includes people walking and cycling. The average campus walk paths and sidewalk capacity is $C_{nm(y)}$. The calibration parameters τ_{nm} and λ can utilize mobility data from any non-motorized activity surveys available, or if guessed, should remain consistent throughout the analysis to provide

insights about the relative effect on mode choice. Sidewalks can become overcrowded between class sessions and significantly impede the flow of foot and bicycle traffic. Very little is available in the literature to model non-motorized capacity, suggesting this is an area for future research.

For relative comparison, the model defines the average travel times for carpool and motorcycles as,

$$IVTT_{cp(y)} = IVTT_{auto(y)} \tag{39}$$

and

$$IVTT_{mc(y)} = IVTT_{auto(y)} \tag{40}$$

because all motorized vehicles in this model will be part of the automobile traffic stream.

Parking demand. The framework defines parking demand as a proportion of the population using automobiles and needing parking where,

$$N_{auto(y)} = PP_{(y)} \frac{(P_{auto(y)} + P_{carpool(y)})}{T_{freq}} \tag{41}$$

Given the parking capacity of Park$_{CP}$ stalls, the parking demand function is,

$$PKD_{(y)} = N_{auto(y)} / Park_{CP} \tag{42}$$

Travel model calibration

The NDSU case study data calibrates trip production rates, trip distribution by average travel time and radial distance, modal split by population percentages, and impedance factors based on

average IVTT and OVTT values for their respective transportation modes.

Trips generated

The faculty and staff population in the survey year was 5,187 and the student population was 12,099. The student trip rates are shown in Table I.

Table I: Campus trip rate distribution

The NDSU survey produced trip rates separately for faculty/staff and students, but because the distributions were similar this analysis will use the student trip rates for the entire NDSU population to describe the aggregate population travel behaviour. The annual average daily trip for this population is,

$$T_{freq} = \sum_{t=1}^{6} t \times \phi_t \qquad (43)$$

where the calibration values are,

$$\phi_1 = 0.11,\ \phi_2 = 0.63,\ \phi_3 = 0.04,\ \phi_4 = 0.18,\ \phi_5 = 0.02,\ \text{and}\ \phi_6 = 0.02 \qquad (44)$$

Evaluating this expression gives an annual average daily trip rate of 1.71 one-way trips per person.

Trip distribution

This trip distribution model requires the average distance travelled from campus by mode. The NDSU survey produced the average travel distance by mode as summarized in Table II and Table III. Without additional fidelity available, the model assigns the average ride distance for motorcycles and carpools to be equal.

Table II: Average drive-alone distance

Table III: Average walk or cycle time

Table IV: Average travel distance by mode

Table IV summarizes the average distances by mode share used for estimating the initial TLFDs to which the model applies a distance shift factor to simulate future sprawling with population growth.

Table V: Summary of calibrated trip frequency distribution estimate by mode

The model calibrates TLFDs for non-motorized, bus, and other motorized modes using the distribution functions and calibrated parameter values shown in Table V. The unusual trip length distribution profile for university trips is an area for further research because the data from all three universities in the area exhibited a similar tri-modal distribution profile.

Mode choice

Table IV summarizes the base year mode share, travel time, and parking demand variables from the NDSU surveys. The IVTT and OVTT are in minutes.

The logit model calibration uses these parameters to produce the parameter values summarized in Table VI.

Table VI: Logit model calibration

The solution converges with high precision for the target mode share values P_j as shown in the last two rows of the table.

General observations of the calibrated parameters are:

(1) The population tends toward automobile use relative to the other modes, with a strong positive bias.

(2) Bias parameter elimination for bus is consistent with the *logit* property that bias will be relative to the other choices available.

(3) Calibration eliminates IVTT for non-motorized modes. This is consistent with the definition that users of non-motorized modes are not travelling *in* a vehicle. The remaining mode users that do travel in a vehicle exhibit a disutility in IVTT.

(4) Calibration eliminates OVTT for automobiles, carpool, and motorcycle, which is intuitive since the model constrains average parking lot access time as a constant throughout the analysis period. Future studies can adjust these parameters to simulate parking stall availability at different distances from the activity centre.

(5) As expected, calibration places a relatively high disutility on parking demand for automobile users. The disutility factor for carpool is smaller, possibly due to its smaller share of users that need parking.

(6) As anticipated, parking demand is a positive utility for average bus and motorcycle users.

(7) Calibration eliminates parking as a factor in non-motorized mode choices. This hints that users of non-motorized modes are also less likely to prefer or afford automobiles, and will likely use bus if walking distances and campus overcrowding further increases OVTT.

Table VII summarizes the direct elasticities for each mode.

Table VII: Direct elasticities of mode choice with mode attributes

These results indicate that automobile modes are inelastic to OVTT but trend negatively with

increases in IVTT and PKD. Bus choice trends negatively with IVTT and OVTT but positively with PDK. Carpool choice trends highly negative with IVTT, is inelastic with OVTT, and trend negatively with PKD. Motorcycle and carpool modes trend similarly negative and are inelastic to OVTT. Motorcycle trends positively with PKD while carpool tends negatively. Non-motorized mode choices are inelastic with IVTT and PKD for this population sample. All of these calibration results validate intuitive reasoning for those choices.

Trip cost

Assigning trip times requires average trip volume information to update the travel time or cost models with every model loop iteration until convergence.

Automobile Travel Time

The average IVTT for drive-alone modes was about 15.98 minutes as shown in Table VIII.

Table VIII: Average drive-alone IVTT

From,

$$IVTT_{auto(y)} = T_{avg\_autoFF(y)}\left[1 + \tau_{auto}\left(\frac{V_{area(y)}}{C_{area}}\right)^4\right] = 15.98 \tag{45}$$

The calibrated, equivalent free flow travel time for the base year, i.e. y = 0 is,

$$T_{avg\_autoFF(0)} = 15.98 \Bigg/ \left(1 + \tau_{auto}\left(\frac{V_{area(0)}}{C_{area(0)}}\right)^4\right) \tag{46}$$

The average, equivalent free-flow travel time could change as the average population driving

distance $D_{avg\_auto(y)}$ shifts such that,

$$IVTT_{auto(y)} = \frac{D_{avg\_auto(y)} \times 60}{SFF_{avg\_autoFF(0)}} \left[1 + \tau_{auto} \left(\frac{V_{area(y)}}{C_{area(y)}} \right)^4 \right] \tag{47}$$

where $SFF_{avg\_auto(0)}$ is the equivalent average speed under non-interfering conditions across all interrupted and uninterrupted flow segments to and from campus in the base year. This value is,

$$SFF_{avg\_auto(0)} = \frac{D_{avg\_auto(0)}}{T_{avg\_auto(0)}} \times 60 \tag{48}$$

which equates to $(4.49/15.98) \times 60 = 16.86$ mph.

The calibration assigns one-minute to out-of-vehicle travel time (OVTT) to simulate a relatively short walk to nearby parking facilities. The OVTT will also be the same for motorcycles that typically park in the same vicinity of automobiles.

Bus travel time calibration. Table IX shows the travel time distribution and average travel time for bus from the NDSU survey.

Table IX: Average bus IVTT

The model assigns this average travel time to calculate the uninterrupted flow time for the base year, thus stipulating that the transit agency will maintain the same schedule performance throughout the analysis year. That is,

$$T_{avg\_bus(0)} = 19.00 \tag{49}$$

The out-of-vehicle travel time (OVTT) for bus combines walk (or bicycling) and wait times.

From the section on non-motorized (nm) calibration, the average walk distance was 0.33 miles. As summarized in Table X the distribution for bus wait time produces an average of 8.37 minutes. This analysis assigns the average OVTT for bus as the sum of the average non-motorized travel time (6.25 minutes) and the average wait time summarized in Table X (8.4 minutes), which is 14.62 minutes.

Table X: Average bus wait-time

This baseline case study will provide a foundation to study how real-time bus-arrival information technology could change convenience factors that affect perceived OVTT, and consequently mode shifting to or from transit.

Non-motorized time. For the 32% using non-motorized modes, the split between walking and cycling is 20% and 12% respectively. If the average walk speed is 2 mph and average cycling speed is 5 mph, then the average non-motorized speed would be (0.20/0.32) (2) + (0.12/0.32) (5) = 3.13 mph. At an average speed of 3.13 mph, the average OVTT for non-motorized modes is 0.33/3.13×60 = 6.25 min.

Trip volumes. As shown in Table XI, the differential F-M population for the survey year was 108,607. The area population grew an average of 1.7% annually since 1980 (USDOC 2010). The most recent trip volume study for the area (ATAC 2008) produced the trip productions and attractions shown. Dividing the trips by the population size produces a trip rate of 13.75. This high rate does not appear to be reasonable based on the Census data hence this study will update the trip rate when new F-M survey results become available. The simulation will use the (NCHRP 1998) trip rate recommendation for the trip T_{FM} parameter. The average trip rate for

the university population was 1.21, which is within the order of the 1.71 ratio for the NDSU survey.

Table XI: F-M area trip statistics in 2005

The trip cost model adds the AADT volume for the differential F-M area to the NDSU trips as a function of population growth for each area. The F-M trips are,

$$PCE_{FM(y)} = PP_{FM(y)} / T_{FM} \qquad (50)$$

Updating the PCE volume changes the V/C ratio for the analysis year, which in turn changes the IVTT. The PCE factors are 1.5 for buses and 0.5 for motorcycles under prevailing traffic volumes and level terrain for the area (TRB 2010). The PCE for trucks in the F-M traffic stream is 1.5 for prevailing volume conditions and mostly level terrain. The model adds truck traffic at 10% of each annual automobile volume increment into the existing F-M traffic stream.

Campus population growth. Based on data from the NDSU Office of the Vice President for Student Affairs, the average annual enrolment growth rate has been 3.9% since 2000 as shown in Figure 1. Given a similar student/faculty-plus-staff ratio policy, the NDSU generated trips for the analysis year *y* is,

$$Trips_{NDSU(y)} = PP_{NDSU(y)} T_{NDSU} \qquad (51)$$

The parking demand function requires the parking capacity and number of permits issued in the base year. The NDSU surveys reported that there were 6,944 permits for 4,157 spots in the base year. Therefore, the parking demand was,

$$PKD_{(y)} = \frac{Autos_{(y)}}{Park_{CP(y)}} \varepsilon_P \qquad (52)$$

where $Autos_{(y)}$ is the number of automobiles, ε_p is the fraction of automobiles that actually have permits to park, and $Park_{CP(y)}$ is the parking capacity for each analysis year. This value is 1.67 for the base year.

Scenario forecasts

This analysis compares three scenarios of population growth and parking supply. These are:

(1) constant parking supply with 2% campus population growth

(2) constant parking supply with 4% campus population growth

(3) parking stalls increase by 20% every five years, attempting to stabilize the demand from 4%t campus population growth

These scenarios hold the OVTT for automobile and carpool users constant to minimize the number of variables, and to provide better insights on the PKD impact. A future supply scenario that is consistent with the third scenario could involve plans to construct a multilevel parking garage that is sufficiently close to the main activity centres on campus.

Constant parking supply and 2% population growth

Figure 5 compares model run results for scenarios of 2% and 4% campus population growth rates. The parking-demand-ratio (PKD) increases from 1.67 in the base year to about 2.25 (with 2% growth) and 3.25 (with 4% growth) within 25 years. This is equivalent to reducing the probability of finding a parking spot by about 15% and 29% respectively.

Figure 5. Parking demand ratio with constant parking supply, 2% and 4% campus population growth

Figure 6. Mode choice mix with constant parking supply and 2% campus population growth

Figure 6 shows the mode share results constant parking supply and 2% population growth rate. The most popular mode shares, automobile and non-motorized, remain dominant, but they invert with increasing parking difficulty. Bus mode share gradually increases while carpool and motor cycle mode shares decline slightly during this analysis period.

Constant parking supply and 4% population growth

Maintaining the historical campus population growth rate at 4% throughout the analysis period produces a very different scenario that exhibits four distinct transitional phases.

Figure 7. Mode choice mix with constant parking supply and 4% campus population growth

The first phase lasts for about 10 years and appears to be a compression of the scenario with 2% population growth. The second phase lasts for about four years where automobile and non-motorized mode shares levels off. The third phase lasts for about four years where the motorcycle, carpool, and automobile shares rise to a peak. Non-motorized share continues to decline during this period because the population is apparently shifting to the motorized modes, likely due to increased crowding on campus. The fourth phase begins a transition that is more characteristic of a dense metropolitan area campus where transit begins to dominate. Near the final horizon years, automobile mode share tends to plateau around 20%, even with continued increase in traffic volume from both the special generator and its metropolitan area. However, the model shows that bus mode share will increase consistently if the transit agencies continue to provide the same level of service.

High parking supply rate and 4% population growth

This scenario simulates a 20% increase in parking stalls every five years. Figure 8 shows that the added supply in each year that a new parking facility opens tends to stabilize the demand on average. However, demand tends to outpace supply during the intervening years until new capacity becomes available.

Figure 8. Parking demand ratio with 20% parking supply increase every five years, and 4% campus population growth

Figure 9. Mode choice mix with twenty percent parking supply increase every five years, and four percent campus population growth

Figure 9 shows the simulation results where attempts to stabilize the parking demand will result in an overall mode mix transition that is similar to the slower population growth scenario. The popular modes will tend to remain dominant on average and eventually invert shares while the population tends to choose the remaining modes with the same share tendencies.

Discussion of findings

The analytical framework developed for this case study differs from the traditional approaches that planners use to forecast trip volumes between origin and destination zones. The goal was to determine the how parking supply impacts campus mode choice with varying levels of parking supply and population growth, including trip impedance factor changes from travelling to and from external zones with growing congestion levels. The analysis utilized a modified four-step travel demand model at the macro level, modified to reduce the amount of data needed to achieve the analysis goals.

Model calibration

Population growth rate relative to parking supply is a significant factor in campus mode choice. However, the NDSU base year survey data strongly influence the simulation results for this case study. Other special traffic generators with different base year demographics and growth will likely observe different results. The trip length distribution for the campus population appeared to be a composite of three distinct distributions that separately describe motorized, non-motorized, and transit modes. The Gamma and Weibull distribution functions appear to describe these distributions fairly well. The multinomial logit model calibration provided intuitive results. In particular, only bus and motorcycle mode choices were positively elastic with parking demand while non-motorized mode choices were inelastic with parking demand.

Simulation scenarios

The three simulated scenarios examined mode mix shifting under constant and high parking supply policies with different campus population growth rates, while maintaining the base year growth rate for the metropolitan area population. Results indicate that without parking supply changes, and maintaining the base year campus population growth rate, the mode mix will transition in four distinct phases. A 50% reduction in campus population growth rate will tend to extend the first of these four phases of the mode share mix throughout the 25 year analysis period. In all cases, the two dominant modes, automobiles and non-motorized, will tend to invert their shares, but remain dominant. Increasing parking stall supply by 20% every five years will tend to stabilize demand, but overall, the mode share mix will revert to the base year tendencies. The main explanation for this is that the population characteristics and choice dispositions remain unchanged from the base year demographics. Hence, the model user should be cautioned

that a simulation for such a long time horizon, without periodic re-calibration with new survey data, will not necessarily capture the changing attitudes of the campus population to yield usable results. Therefore, the planner should consider only the first five years of simulation results when considering policy alternatives.

Improvement scenarios

Model refinement is possible by incorporating additional mode choice attributes and user characteristics into the utility functions. Such attributes would include factors that relate to mode choice affordability, for example, income level and fuel prices. Factors that relate to mode choice reliability include vehicle maintenance and bus schedule. Climate can also be a significant factor in mode choice. Some individuals may simply prefer to drive less during the winter and some may prefer to walk less in sub-zero temperatures. In addition, population groups that have certain handicaps may eliminate a transportation mode from the choice group. Also, users that prefer to live off-campus and seek affordable housing further away would likely prefer to drive. The availability of real-time information technology to inform users about bus arrival times or parking spot availability may change a user's perception about the cost and convenience of a particular mode. An exhaustive list of the factors that affect mode choice is outside of this case study scope but could later reveal how effectively bias parameters incorporate them, without masking their impact on the parking issue.

Conclusions

This research developed an analytical model to examine a specific transportation related issue within a special generator zone when only limited and aggregate knowledge about the external zones is available or affordable. The main goal was to determine how parking supply changes

and population growth affect transportation mode mix for a special generator campus, and in this case, the NDSU campus survey data calibrated the models. The objectives of this case study were to develop a low-cost methodology and analytical framework that minimize the amount of data collection required for model calibration while providing an ability to simulate realistic scenarios for any number of horizon years. The resulting model utilized aggregate survey information about the zone's trip generation characteristics and trip length frequency distribution from campus by transportation mode. The analytical framework combined mathematical modelling with software programming to achieve the goals and objectives. The results illustrate that the framework is low-cost and effective for analysing mode choice changes under different scenarios, including varying rates of parking supply and population growth.

Implications and recommendations

The model provides insights that would benefit campus planners and employers with facilities that share similar trip generation and attraction characteristics. The information is useful in recruitment and target market development. However, the user and decision makers must be aware that mathematical models attempt to describe the overall behaviour of an aggregate population and do not predict individual human behaviour. Therefore, planners must re-recalibrate the model with new survey data within four years and sparingly use trend information beyond five to ten years.

Future research

Information about trip length frequency distribution by mode will improve the model calibration. The NDSU data revealed a tri-modal, composite distribution that differs significantly from others that tend to exhibit a single mode distribution for the aggregate population, even when separating

the trips by purpose. This case study establishes a baseline for future analysis of how advanced information technology will affect mode choice. For example, understanding the elasticity of mode choice with the availability of real-time information technology on mobile devices can help agencies evaluate technology alternatives for improving service at reduced cost. Given the significance of convenience as a factor in mode choice, technologies that provide real-time alerts about transit arrival and parking spot availability could change the results of the scenarios forecasted.

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Table I. Campus trip rate distribution

Portion (%)	One-way Trips
11	1
63	2
4	3
18	4
2	5
2	6

Table II. Average drive-alone distance

Mile	Percent	Product
1.00	0.04	0.04
2.00	0.16	0.32
5.00	0.70	3.51
6.00	0.11	0.63
Weighted Average		4.49

Table III. Average walk or cycle time

Mile	Percent	Product
0.25	0.70	0.17
0.50	0.30	0.15
Weighted Average		0.33

Table IV. Average travel distance by mode

Mode	Share	Distance (miles)	IVTT (min)	OVTT (min)	PKD
Automobile	0.53	4.49	15.98	1.00	1.67
Bus	0.07	1.50	17.1	14.62	1.67
Carpool	0.04	4.49	15.98	1.00	1.67
Motorcycle	0.04	4.49	15.98	1.00	1.67
Non-motorized	0.32	0.33	0.00	6.25	1.67

Table V. Summary of calibrated trip frequency distribution estimate by mode

Mode Type	Distribution Type	Parameter Values
Non-motorized	Gamma	$A_{nm} = 0.3$, $\beta_{nm} = 0.512$, $\gamma_{nm} = 2.9$
Bus	Weibull	$A_{bus} = 0.11$, $k_{bus} = 1.8$, $\lambda_{bus} = 3.1$
Automobile Carpool Motorcycle	Weibull	$A_{auto} = 0.62$, $k_{auto} = 8.9$, $\lambda_{auto} = 5.1$

Table VI. Logit model calibration

Automobile		Bus		Carpool		Motorcycle		Non-Motorized	
$\alpha0(0)$	1.0702	$\alpha0(1)$	0.0000	$\alpha0(2)$	-0.0095	$\alpha0(3)$	-0.0095	$\alpha0(4)$	-0.0335
$\alpha1(0)$	-1.2900	$\alpha1(1)$	-0.2885	$\alpha1(2)$	-1.5380	$\alpha1(3)$	-1.5786	$\alpha1(4)$	0.0000
$\alpha2(0)$	0.0000	$\alpha2(1)$	-1.4211	$\alpha2(2)$	0.0000	$\alpha2(3)$	0.0000	$\alpha2(4)$	-3.6766
$\alpha3(0)$	-1.7747	$\alpha3(1)$	1.0331	$\alpha3(2)$	-0.3024	$\alpha3(3)$	0.0863	$\alpha3(4)$	0.0000
IVTT	15.98	IVTT	19.00	IVTT	15.98	IVTT	15.98	IVTT	0
OVTT	1.00	OVTT	14.62	OVTT	1.00	OVTT	1.00	OVTT	6.25
PKD	1.670	PKD	1.670	PKD	1.670	PKD	1.670	PKD	1.670

Vj	-22.5079		-24.5323		-25.0919		-25.0919		-23.0124
Exp(Vj)	1.679E-10		2.217E-11		1.267E-11		1.267E-11		1.013E-10
LN(Pj)	-0.63		-2.66		-3.22		-3.22		-1.14
Pj Target	0.53		0.07		0.04		0.04		0.32
Pj Logit	0.530000		0.070000		0.040000		0.040000		0.320000

Table VII. Direct elasticities of mode choice with mode attributes

	Auto		Bus		CP		MC		NM
IVTT	-9.6884		-5.0984		-23.5941		-24.2175		0.0000
OVTT	0.0000		-19.3216		0.0000		0.0000		-15.6257
PKD	-1.3933		1.6049		-0.4850		0.1384		0.0000

Table VIII. Average drive-alone IVTT

Minutes	Percent	Product
10.00	0.45	4.53
19.00	0.44	8.40
29.00	0.11	3.05
Weighted Average		15.98

Table IX. Average bus IVTT

Minutes	Percent	Product
10.00	0.40	4.00
20.00	0.30	6.00
30.00	0.30	9.00
Weighted Average		19.00

Table X. Average bus wait-time

Minutes	Percent	Product
7.00	0.68	4.76
10.00	0.23	2.30
12.00	0.03	0.36
15.00	0.05	0.75
20.00	0.01	0.20
Weighted (minutes)		8.37

Table XI. F-M area trip statistics in 2005

Category	FM Area-Balanced		NDSU-Unbalanced	
	P	A	P	A
HBW	159,347	159,347	460	3,517
HBO	452,513	452,513	1,064	5,158
NHB	99,546	99,546	1,993	1,993
HBS-University	9,942	9,942	345	6,370
HBS-High School	9,027	9,027		
HBS-Grade School	20,185	20,185		
Area Total Trips	1,501,120		20,900	
Area Diff Trips	1,493,396			
2005 Populaton	125,893		17,286	
Area Diff Pop	108,607			
Trip Rate	13.75		1.21	

Figure 1. NDSU annual enrolment and average growth rate.
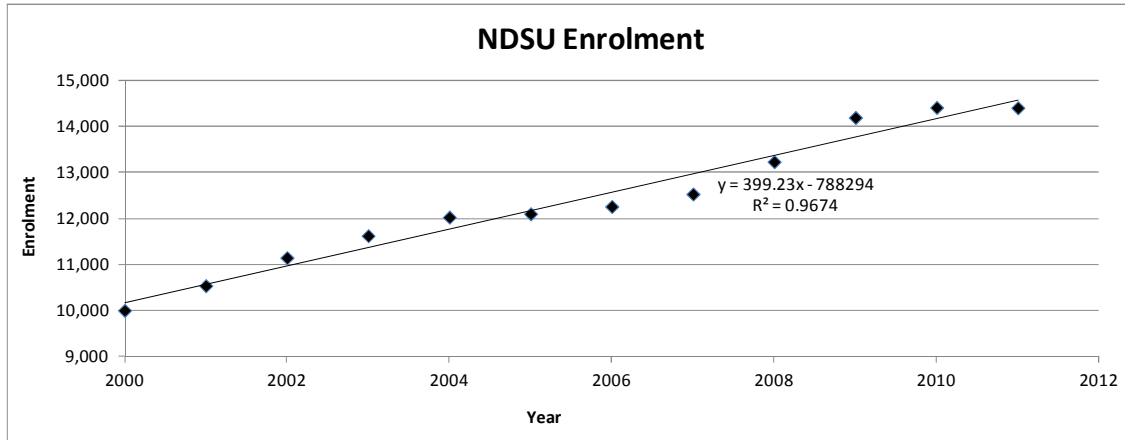
Figure 2. Parking demand model configuration.
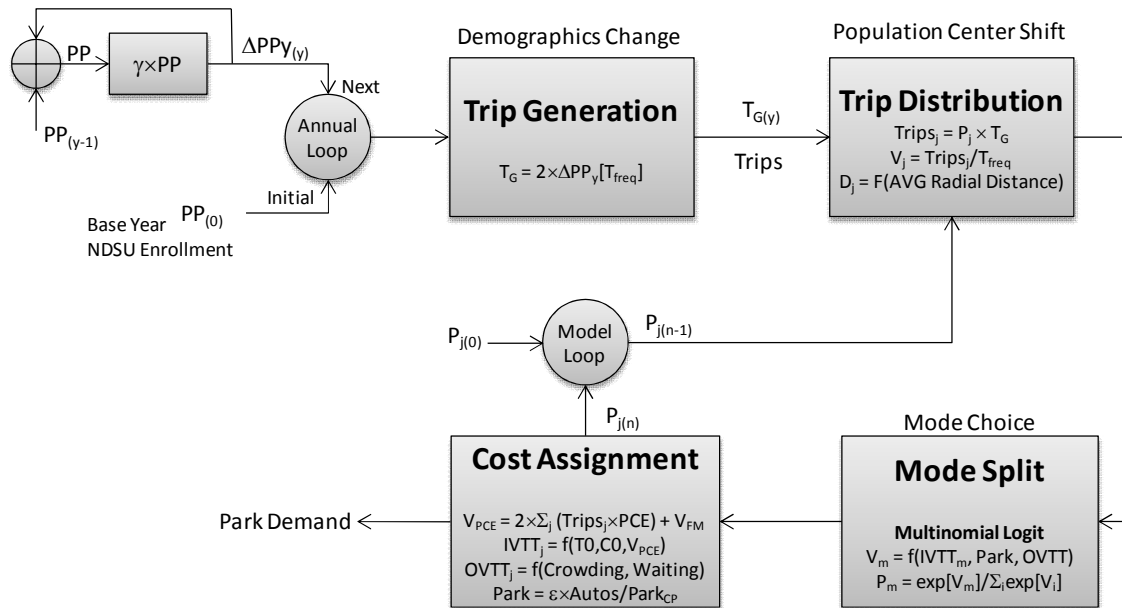
Figure 3(a). Trip length distribution.
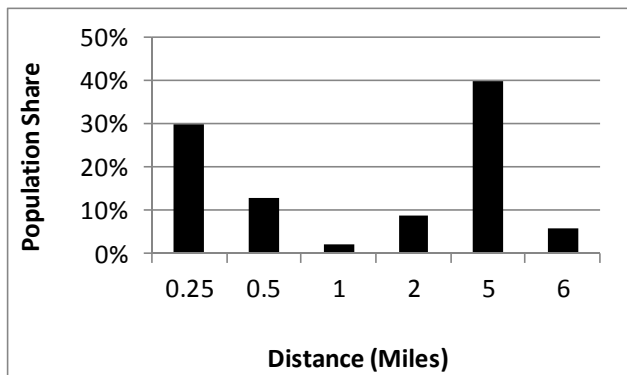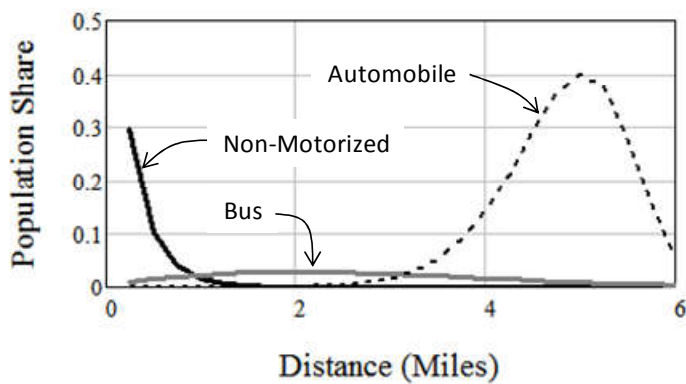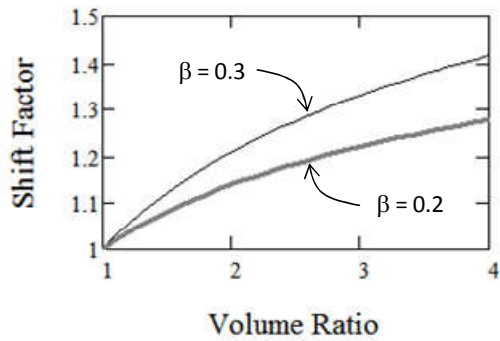

Figure 3(b). Joint distribution model.

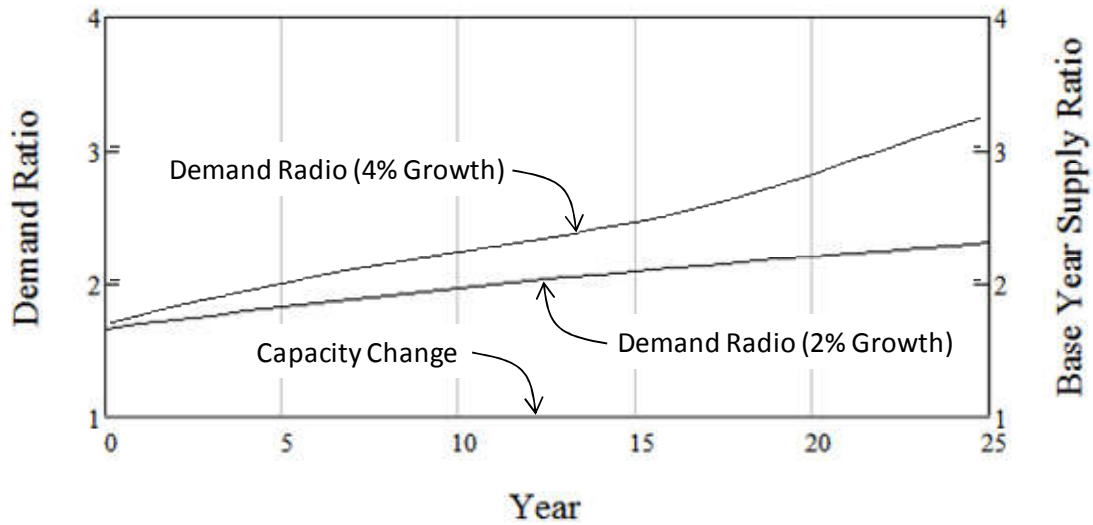Figure 4. Comparison of population shift factors.

Figure 5. Parking demand ratio with constant parking supply, 2% and 4% campus population growth.

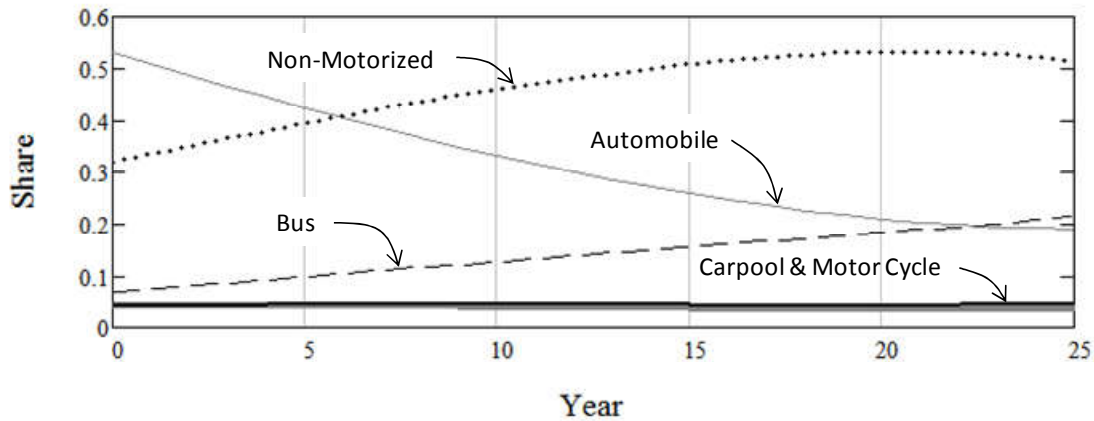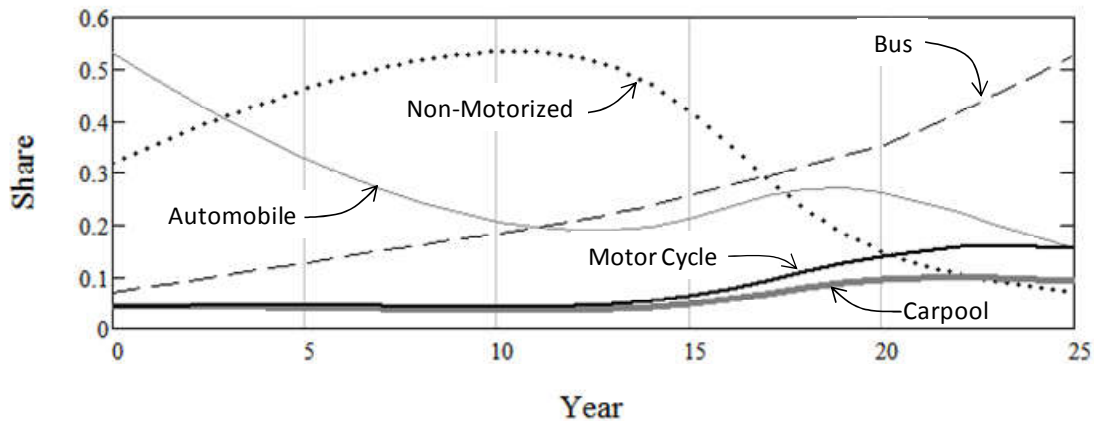Figure 6. Mode choice mix with constant parking supply and 2% campus population growth.

Figure 7. Mode choice mix with constant parking supply and 4% campus population growth.

Figure 8. Parking demand ratio with 20% parking supply increase every five years, and 4% campus population growth.
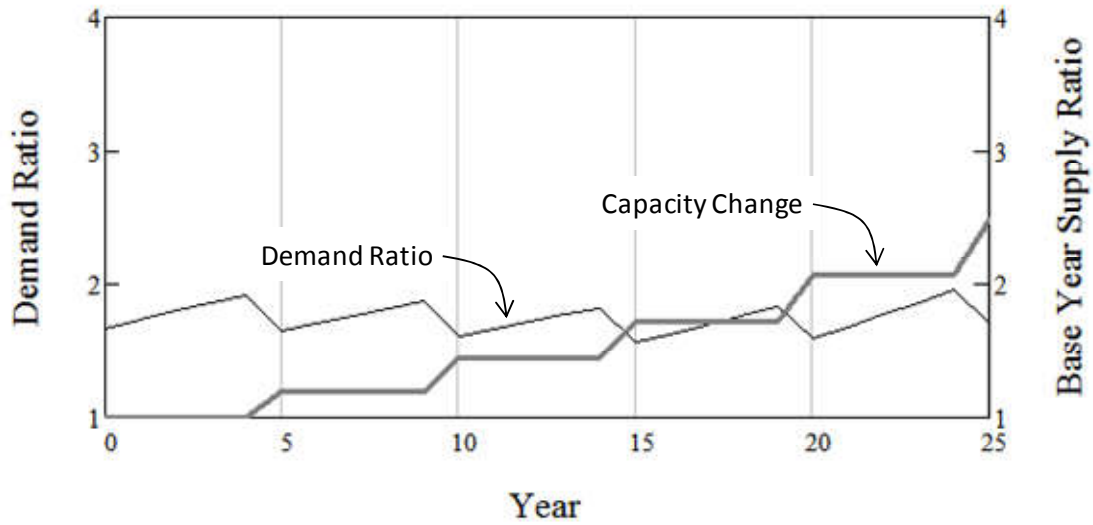

Figure 9. Mode choice mix with twenty percent parking supply increase every five years, and four percent campus population growth.