# CENTRAL DAKOTA 2025 BASE TRAVEL DEMAND MODEL DEVELOPMENT AND CALIBRATION

FINAL REPORT

# To the Central Dakota MPO

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# 1. INTRODUCTION

The Central Dakota MPO, which includes the cities of Minot, Surrey, and Burlington, has been developing a Travel Demand Model (TDM) to incorporate new data, reflect current travel patterns, and integrate advancements in transportation modeling techniques. The updated model is based on 2024 data, ensuring that it accurately represents the region's transportation system.

The model follows the four-step TDM process, which includes trip generation, trip distribution, mode choice (modal split), and trip assignment. Each step is calibrated to reflect real-world travel behavior, allowing for accurate forecasts of traffic demand. The model update process involves adjusting key input parameters and validating the model's outputs against observed traffic data to ensure alignment with actual conditions.

Model calibration is an iterative process, as shown in Figure 1, where parameters are refined in multiple stages until the model meets acceptable accuracy standards. This approach ensures that the model is not only a reliable representation of current conditions but also a powerful tool for forecasting future transportation needs and supporting informed decision-making.

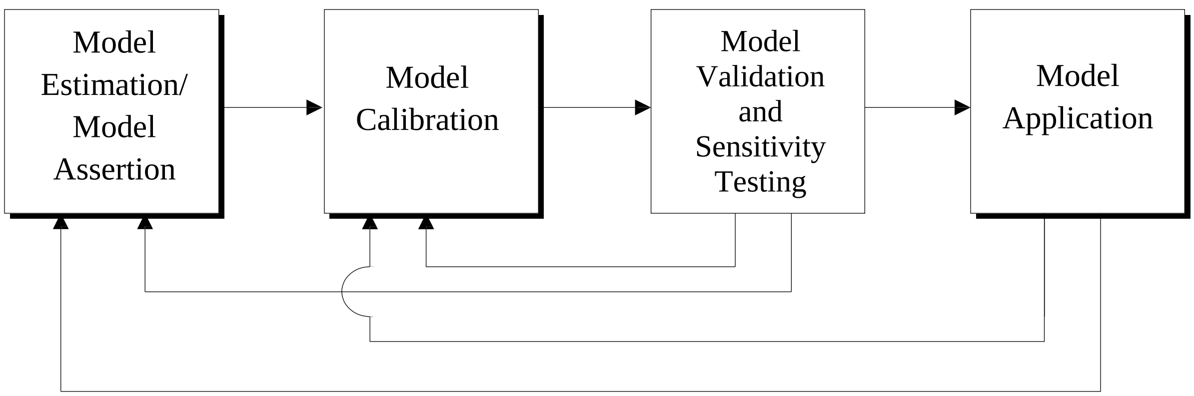


**Figure 1 Central Dakota TDM Calibration Flow Chart**

The rest of this document describes the model update process including the data, methods, and models that were used to develop the model. Chapter 2 discusses the development of the 2024 TDM; Chapter 3 discusses the capacity calculation methodology; Chapter 4 discusses the input data used in the model; Chapter 5 summarizes the trip generation models and methods; Chapter 6 discusses the trip distribution step; Chapter 7 discusses the trip assignment step; Chapter 8 discusses the model calibration, validation, and output.

# 2. MODEL INPUT DATA

The main data used as input to the model are the network and socioeconomic data. The two datasets were developed through a collaborative effort between MPO staff and ATAC. These data are discussed next.

## 2.1. Transportation Network Data

The transportation network is an abstract representation of the transportation system that has essential data describing the available transportation supply. The network is maintained in GIS as a geodatabase that contains four feature classes. These feature classes included: links that represent the roadway, nodes that represent intersections, centroids which are the trip origin/destination points for transportation analysis zones (TAZs), and external centroids which are external loading trip points. The network was updated by ATAC and the MPO to represent 2022 base year conditions.

The main attributes of the network that are used in the model include the network geometries (number of lanes and turn lanes), posted and Free Flow Speeds, functional classification, length of links, link ADTs (passenger and truck counts), link location area type and the intersection controls.

### 2.1.1. Distribution of Modeled Network by Functional Classifications

Table 1 shows the percentage of centerline miles by functional class.

**Table 1 Centerline Miles Distribution by Functional Classification**

| Functional Class | Centerline Miles | Percentage |
|---|---|---|
| **Freeway** | 30.23 | 14.08% |
| **Expressway** | 18.91 | 8.81% |
| **Principal Arterial** | 10.70 | 4.98% |
| **Minor Arterial** | 45.02 | 20.97% |
| **Collectors** | 41.40 | 19.28% |
| **Local Roads** | 0.84 | 0.39% |
| **Ramps** | 3.62 | 1.69% |
| **Centroid Connectors** | 63.96 | 29.79% |
| **Total** | 214.68 | 100% |

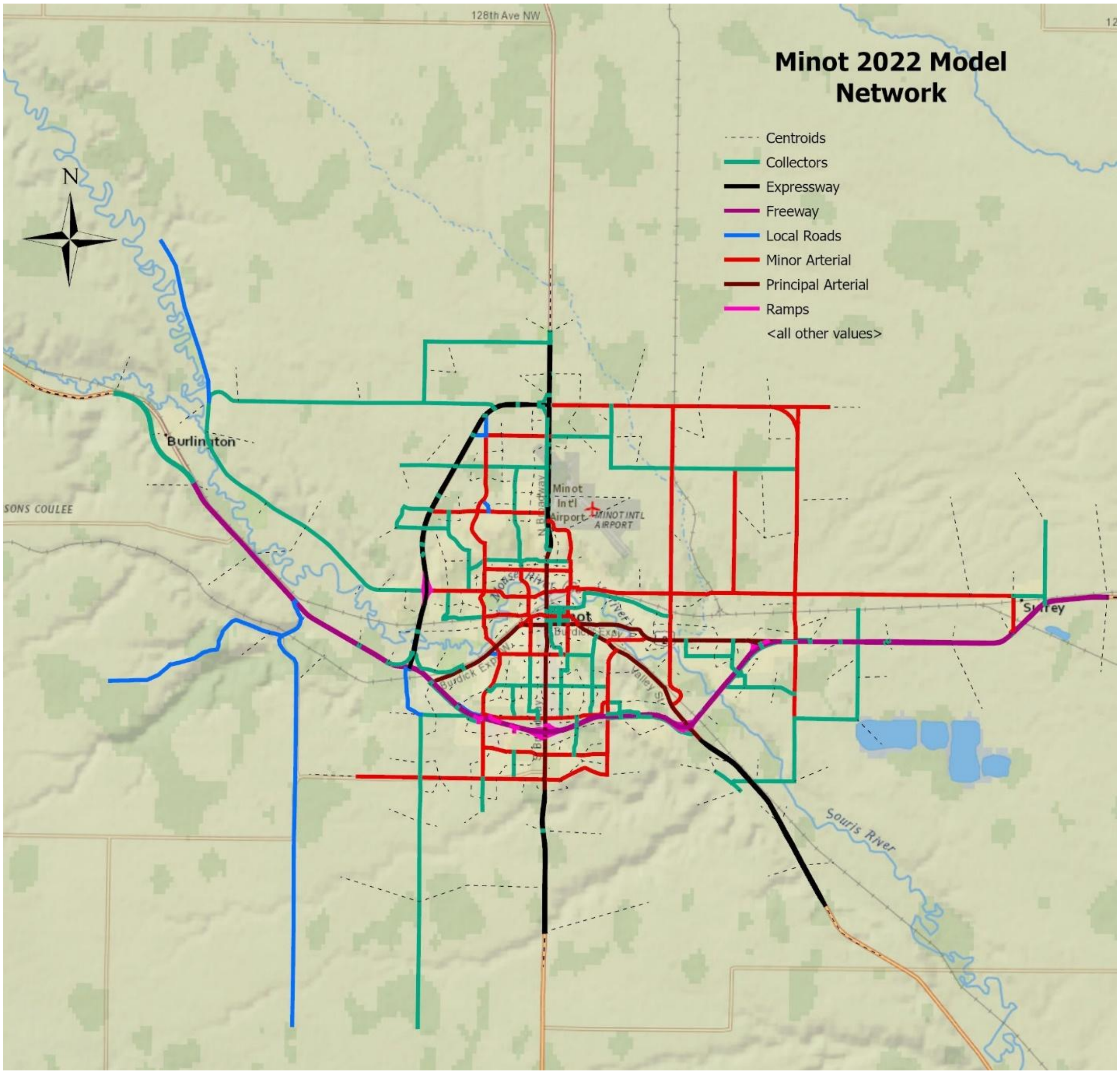


**Figure 2 Minot 2022 Model Network**

Figure 2 shows the modeled network distribution by functional class with centroid connectors.

## 2.2. Socioeconomic Data

Socioeconomic data are used to generate the total number of trips produced and attracted by each TAZ in the TDM. The TAZ geographies were developed by a collaborative effort between MPO staff and the ATAC. The socioeconomic data included within each TAZ were collected from a third-party vendor named Data Axle. The gaps in the socio-economic data (especially the household numbers) were mitigated by collaborative efforts between MPO staff and ATAC. The socioeconomic data that was used in the model is described next.

### 2.2.1. TAZ Geography Files

A total of 232 internal TAZs were used for the 2022 model. Several TAZs were modified (split or merged) based on input from both the MPO and ATAC.

### 2.2.2. Socioeconomic Data TAZ Attributes

The socioeconomic data within the TAZ contained the following fields

#### *2.2.2.1. Number of Persons per household in each TAZ according to the following categories (attributes)*

1. # of single-family households
2. # of multi-family households
3. Total number of households

#### *2.2.2.2. School-age children per household in each TAZ in four categories[1]*

1. # of Grade school-age children
2. # of Middle age school children
3. # of High school age children
4. # of College age (20-24)

#### *2.2.2.3. Employment data (# for each TAZ)[2]*

1. Manufacturing/Industrial (NAICS 31-33)
2. Construction and resources/Commercial (NAICS 21, 23)
3. Retail/Office (NAICS 44-45)
4. Service (NAICS 52,53,55,56,56,51,62,71,81,99)
5. Education (NAICS 61) with the following additional fields
    a. Elementary school enrollment for each TAZ
    b. Middle school enrollment for each TAZ
    c. High school enrollment for each TAZ

[2] Data has been disaggregated (Previously, it included retail, other and service jobs)

#### *2.2.2.4. Enplanements*

Yearly enplanements borrowed from Piedmont Triad Regional Model NC, sourced from Minnesota/St. Paul region observed data from the airport.

#### *2.2.2.5. Special generators*

Special generator TAZS for Minot airport.

#### *2.2.2.6. ADT at external locations*

Used as estimates of trips with at least one trip ending outside the MPO area.

# 3. TRIP GENERATION

Trip generation is the first step in the Travel Demand Model (TDM) and is responsible for estimating the number of trips originating from and destined for each Traffic Analysis Zone (TAZ). This process utilizes the socioeconomic data outlined in Chapter 4, combined with regression parameters, to determine trip production and attraction levels for each TAZ.

Typically, trip production is influenced by household characteristics within a given TAZ, while trip attraction is primarily driven by employment levels in the zone. A key enhancement in this model is the incorporation of long-haul freight movements, which adds greater accuracy to trip estimates.

The following sections provide a detailed explanation of the trip generation methodologies applied in this model, along with a discussion of the results.

## 3.1. Internal-Internal Passenger Vehicle Trip Purposes

Internal-Internal (II) passenger vehicle trips refer to trips that both originate and terminate within the **Metropolitan Planning Organization (MPO)** area for Passenger Vehicles. These trips are categorized based on their purpose into six primary classifications:

- **Home-Based Work (HBW)** – Trips between home and workplace.
- **Home-Based Shopping (HB-Shop)** – Trips originating from home for shopping purposes.
- **Home-Based Other (HBO)** – Trips from home to various non-work, non-shopping destinations (e.g., recreation, personal errands).
- **Home-Based School K-12 (HB-School K-12)** – Trips from home to primary and secondary schools.
- **Home-Based University (HBU)** – Trips from home to universities and colleges.
- **Non-Home-Based (NHB)** – Trips that do not originate or end at home, such as work-to-shop or work-to-recreation trips.

### 3.1.1. Trip Productions

Table 2 presents the trip generation equations used to develop the II trip production table showing the regression parameters applied in these equations. These parameters were initially derived from NCHRP Report 716, a widely used reference for trip generation methodologies.

The model parameters obtained from NCHRP 716 served as the initial basis for trip production estimates. However, these equations were further refined during the calibration process to account for variations in travel behavior across different area types (e.g., urban, suburban, rural).

Adjustments were made to ensure that the final trip generation estimates aligned with observed traffic counts from the trip assignment step, improving the accuracy of the model in reflecting real-world conditions.

**Table 2 Internal-Internal Trip Generation Equations**

| Purpose | Single-Family Households | Multi-Family Households | Overall |
|---|---|---|---|
| **HBW** | **2.76** | **2.33** | **2.55** |
| **HBS** | **1.16** | **0.82** | **0.99** |
| **HBR** | **1.54** | **1.11** | **1.33** |
| **HBO** | **2.28** | **1.11** | **1.70** |
| **NHB** | **4.01** | **2.76** | **3.39** |

### 3.1.2. Trip Attractions

Trip attractions represent the number of trips drawn to each Traffic Analysis Zone (TAZ) based on various factors, primarily employment levels and institutional size (such as school enrollments). These estimates are essential for understanding travel demand patterns, as they help define where trips are likely to end within the model area in Table 3. While the socioeconomic dataset initially contained a variety of job classifications, these were aggregated into broader employment categories to streamline the modeling process. The categories used for trip attraction estimates are summarized in Table 3 which were derived from NCHRP Report 718, a key reference for travel demand modeling.

As with trip production, the initial trip attraction estimates were refined through model calibration to reflect observed travel patterns accurately. Adjustments were made to account for variations in trip-making behavior across different land-use types and geographic areas. These refinements ensured that the trip assignment step produced traffic volumes that closely matched real-world traffic counts, improving the overall reliability of the model.

**Table 3 Trip Attraction Rates**

| Purpose | Industry | Commercial | Office | Service |
|---|---|---|---|---|
| **HBW** | 2.26 | 1.65 | 0.58 | 1.97 |
| **HBS** | - | 3.09 | - | - |
| **HBR** | - | 2.37 | - | - |
| **HBO** | 0.0 | 1.56 | 0.52 | 1.65 |
| **NHB** | 0.4 | 4.88 | 1.45 | 1.23 |

School trip attraction rates play a critical role in accurately estimating travel demand associated with educational institutions. These rates help determine the number of trips attracted to schools based on factors such as student enrollment and facility size.

Table 4 presents the school trip attraction rates per student used in the model, which were sourced from the Institute of Transportation Engineers (ITE) Trip Generation Manual, 11th Edition. The ITE manual is a widely recognized resource that provides empirically derived trip generation rates for various land uses, including K-12 schools, colleges, and universities.

**Table 4 School Trip Attraction Rates Per Student**

| School | Rate |
|---|---|
| **Elementary** | 1.05 |
| **Middle** | 1.05 |
| **High** | 1.05 |

## 3.2. Total Productions and Attractions

### 3.2.1. Internal Productions and Attractions

The total number of trip productions and attractions provides a summary of travel demand within the model area, categorized by trip purpose. These values represent the total trips estimated by the model and serve as the foundation for subsequent steps in the travel demand forecasting process, including trip distribution, mode choice, and assignment.

Since trip productions and attractions must be balanced for internal trips within the study area, the values for each purpose are equal. These totals were derived from the calibrated trip generation model and ensure that the demand estimates align with observed travel patterns. Table 5 shows the total trip productions and attractions according to trip purposes generated from the model for internal trips.

**Table 5 Total Internal Trip Productions and Attractions**

| Purpose | Trip Production | Trip Attraction |
|---|---|---|
| **HBW** | 45,945 | 45,945 |
| **HBS** | 18,394 | 18,394 |
| **HBR** | 24,543 | 24,543 |
| **HBO** | 33,270 | 33,270 |
| **NHB** | 63,158 | 63,158 |

### 3.2.2. External Productions and attractions

External trips—those originating from or destined for locations outside the model area—were estimated based on observed traffic counts at external locations**.** These external trips provide insight into regional connectivity and external influences on the transportation network. Traffic counts were used to validate the external trip estimates, ensuring that model projections align with observed travel volumes. The external stations with nonzero trip productions and attractions represent key regional access points, contributing to both commuter and freight movement. Table 6 shows the total trip productions and attractions that occurred at the external zones (external trips).

**Table 6 Total External Trip Productions and Attractions**

| TAZ Number | External Location | Trip Production | Trip Attraction | Traffic Counts |
|---|---|---|---|---|
| **280** | **US 83 North** | 5,468 | 5,468 | 10935 |
| **281** | **CR 10** | 0 | 0 | 0 |
| **282** | **US 2 East** | 2,463 | 2,463 | 4925 |
| **283** | **US 52 East** | 2,273 | 2,273 | 4555 |
| **284** | **US 83 South** | 3,913 | 3,913 | 7825 |
| **285** | **62nd St SW** | 175 | 175 | 350 |
| **286** | **US 2 West** | 3,638 | 3,638 | 7275 |
| **287** | **22nd St SW** | 0 | 0 | 0 |
| **288** | **16th St SW** | 460 | 460 | 920 |
| **289** | **CH15** | 80 | 80 | 160 |

The outputs from the trip generation step serve as the foundation for the next stage of the travel demand modeling process: trip distribution. In this step, the total trip productions and attractions estimated for each Traffic Analysis Zone (TAZ) are used to determine the likely origins and destinations of trips within the model area.

# 4. TRIP DISTRIBUTION

The trip distribution step takes the trip productions and attractions developed in the trip generation step and assigns them between Origin-Destination pairs. This step helps establish travel patterns by predicting where trips will go based on various influencing factors. For the Central Dakota MPO, the gravity model was used to distribute trips.

This method is based on the principle that trip interaction between two zones is directly proportional to the number of trip productions and attractions and inversely proportional to the travel impedance or travel distance or time between them. The gravity model assigns trips based on the number of productions, attractions, a friction factor (F), and a scaling factor (K).

The friction factor i represents the resistance to travel between two zones. It is inversely proportional to travel distance, time, or cost, meaning that as travel impedance increases, the likelihood of a trip occurring between those two zones decreases. Friction factors are typically derived from observed travel behavior data and can be calibrated using trip length frequency distributions to ensure realistic trip interactions in the model.

The gravity model formulation used in this travel demand model follows the standard structure, with calibrated friction factors and K-factors applied to refine trip distribution.

Equation 1 shows the gravity model formulation used in the model.

**Equation 1 Gravity Model Used for Trip Distribution**

$$T_{ij} = P_i \frac{K_{ij} A_j F_{ij}}{\sum K_{ij} A_j F_{ij}}$$

Where:

$T_{ij}$ = Number of trips assigned between Zones i and j;

$P_i$ = Number of Productions in Zone i;

$A_j$ = Number of Attractions in Zone j;

$F_{ij}$ = Friction Factor; and

$K_{ij}$ = Scaling factor used in calibration to influence specific ij pairs

The typical output of the trip distribution step in TDMs is a matrix showing the origins and destination of each trip. The gravity model uses the trip generation outputs (production and attractions by trip purpose for each zone), a measure of travel impedance between each zonal pair (travel time), and socioeconomic/area characteristic variables (“K-factor”) variables as input. The K-factor is used to account for the effects of variables other than travel impedance in the model. The OD data were used to develop K-factor matrices imputed in the trip gravity model that was used for distributing IE/EI trips. For the TDM, trips were distributed separately for the different periods.

For K-12 school trip distribution, school zones were used to assign trips for Minot Public Schools. The gravity model was used to distribute private school trips.

The output from the trip distribution step is an Origin-Destination matrix showing the number of trips between origins and destinations for each trip purpose. The OD for each trip purpose is summed together to produce a daily OD matrix which is then used to assign trips between each OD pair in the trip assignment step.

# 5. TRIP ASSIGNMENT

Trip assignment is the final computational step in the travel demand modeling process. This step determines the specific routes that trips will take within the transportation network based on the origin-destination (O-D) matrix derived from the trip distribution step. By assigning trips to specific paths, the model can estimate traffic volumes on roadway links, helping planners evaluate network performance and congestion levels. The model assigns trips separately for automobile and truck travel, reflecting their distinct characteristics and operational behaviors. To account for the larger size and different operating conditions of trucks, a Passenger Car Equivalent (PCE) factor of 1.5 was applied to truck trips. This adjustment ensures that truck traffic has an appropriate impact on congestion and roadway capacity calculations.

The User Equilibrium (UE) traffic assignment method was implemented in the model. Under this method, road users independently select the route that minimizes their own travel cost or time, without considering the overall system efficiency. This behavior results in a traffic pattern where no traveler can reduce their travel time by switching routes, leading to what is known as a Wardrop User Equilibrium condition.

The travel cost formulation used in the equilibrium assignment method accounts for key factors influencing route choice, including link travel time**,** perceived distance cost, and congestion effects. These factors ensure that assigned trips realistically reflect how road users make routing decisions under varying traffic conditions and are shown in Equation 2. It takes into account the link travel time, the value of travel time, and the link distance.

**Equation 2 Trip Assignment Cost Equation**

$$TC = TIME\ +\ DISTANCE * 0.35$$

Where:

TC = Link Travel

TIME = Congested travel time

$Distance * 0.35$ = Link length times a perception factor of length compared to travel time, which represents how travelers weigh distance relative to travel time when making routing decisions.

## 5.1. Congested Travel Time Calculations

The Bureau of Public Roads (BPR) function is a widely used formula in traffic assignment models to estimate how congestion affects travel time on roadway links. It accounts for the relationship between traffic volume and roadway capacity, helping simulate real-world congestion and its impact on travel behavior.

The BPR function is expressed as:

**Equation 3 Trip Assignment Cost Equation**

$$T_c = T_f \left[ 1 + \alpha \left( \frac{V}{C} \right)^{\beta} \right]$$

Where:

$T_c$ = Congested travel time (the actual time required to travel a roadway segment under current traffic conditions).

$T_f$ = Free-flow travel time (the time required to travel the segment under ideal, uncongested conditions).

V = Traffic volume on the roadway segment.

C = Capacity of the roadway segment (i.e., the maximum number of vehicles the road can accommodate).

α, $\beta$ = Calibration parameters that determine how congestion affects travel time (varies by roadway functional class).

## 5.2. Capacity Calculations

Capacity is a fundamental component of Travel Demand Modeling (TDM) as it directly impacts both Level of Service (LOS) calculations and trip assignment procedures. In the assignment step, traffic is allocated based on the Volume-to-Capacity (V/C) ratio of each roadway link. As congestion increases (higher V/C values), excess traffic is redistributed to alternative routes to reflect realistic traffic conditions. The Transportation Research Board 2010 defined capacity as follows: “The capacity of a system element is the maximum sustainable hourly flow rate which persons or vehicles reasonably can be expected to traverse a point or a uniform section of a lane or roadway during a given period under prevailing roadway, environmental, traffic, and control conditions. Capacity analysis examines roadway elements under uniform traffic, roadway, and control conditions.”

NCHRP 716 defined on the other hand “Capacity” in a traffic engineering sense is not necessarily the same as the capacity variable used in travel demand model networks. In early travel models, the capacity variable used in such volume-delay functions as the BPR formula represented the volume at Level of Service (LOS) C; whereas, in traffic engineering, the term “capacity” traditionally referred to the volume at LOS E.”

### 5.2.1. Hourly Capacity Calculations for Lanes

The formulas for calculating the hourly capacities for lanes are shown next:

***1. Base Saturation Flow Rate, So***

Following the HPMS procedure, the base saturation flow rate was set at 2,200 for functional class Freeway, 1,400 for Expressway, 1,100 for Principal Arterial, 700 for Minor Arterial, 650 for Collector, 600 for Local, 1300 for Ramp, 600 for Frontage Road passenger car per hour per lane (pcphpl).

### 5.2.2. Hourly Capacity Calculation

After estimating the saturation flow rate for each lane group, the hourly capacity for each functional class is calculated. This calculation is done by multiplying the saturation flow rate by the lanegroup of each functional class. The hourly capacity of each lane group is added to calculate the total hourly capacity. Equation 4 is used for the calculation.

**Equation 4**

$$H_{SI} = \sum Si * Li$$

Where:

$H_{SI}$ is hourly capacity,

$S_i$ represents the saturation flow rate for lane group i and

Li represents the lane group for functional class i.

## 5.3. Daily Capacity Calculations for Lanes

The daily capacity of a roadway is derived by multiplying hourly capacity by 8 hours, assuming peak-hour demand represents approximately 8 hours of daily traffic.

**Equation 5**

$$D_{SI} = H_{SI} * 8$$

Where:

$D_{SI}$ is hourly capacity,

$H_{SI}$ is hourly capacity.

By integrating capacity calculations into the TDM framework**,** the model provides a realistic representation of traffic flow, congestion, and roadway performance, supporting data-driven transportation planning and decision-making**.**

# 6. VALIDATION AND CALIBRATION

Model calibration is a critical step in the travel demand modeling process, ensuring that the model accurately represents real-world travel behavior for a designated base year. The goal of calibration is to fine-tune the model by adjusting input parameters until the model's outputs closely match observed data.

Calibration involves modifying key parameters, including:

- Trip Generation Rates – Adjusting production and attraction values to reflect actual travel demand.
- Node Delays – Refining intersection and control delays to match observed congestion levels.
- Free-Flow Speeds – Ensuring roadway speeds align with field-measured speeds under uncongested conditions.
- K-Factors – Adjusting scaling factors in trip distribution to capture regional travel patterns and observed trip flows.
- Friction Factors – Refining impedance factors in the gravity model to ensure realistic trip length distributions.

Figure 3 shows the calibration and validation flow chart that was used for the model. It was an iterative process that involved adjusting the model parameters until a certain level of confidence in the model's replication of real-world data was achieved.

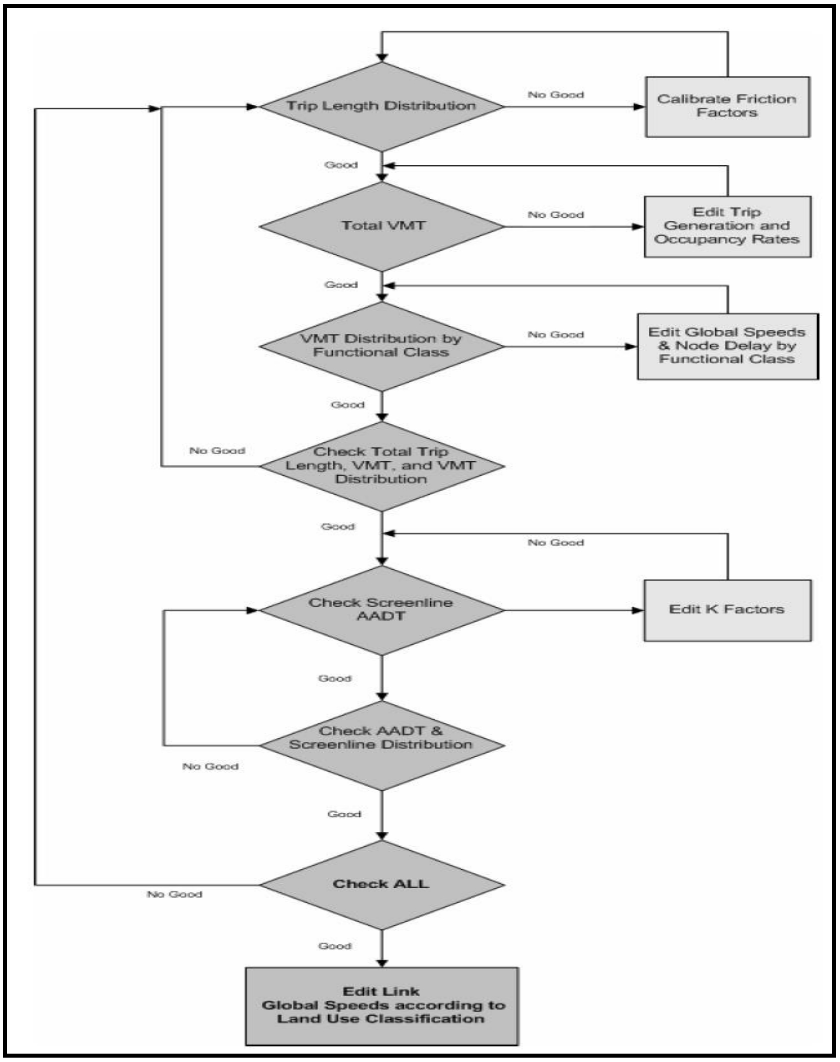


**Figure 3 Calibration Flow Chart**

Once the model has been calibrated, the validation process compares the base year calibrated model outputs to independent observed datasets. Validation helps confirm whether the model is accurately predicting travel demand and network conditions. Ideally, validation should be performed using data sets that were not used in the calibration process to ensure the model's predictive robustness. However, in some cases, this is not feasible due to the limited availability of independent data sources. Consequently, calibration and validation often proceed in parallel, forming an iterative process that refines model parameters until an acceptable level of accuracy is reached. The next sections describe the different model parameters that were used for model calibration and validation.

## 6.1. Trip Length Frequency Calibration and Validation

Trip length frequency distributions illustrate how sensitive travelers are to travel time, varying by trip purpose. These distributions help determine the likelihood of making shorter vs. longer trips based on real-world travel behavior. Steeper trip length frequency curves indicate that travelers are highly sensitive to travel time, meaning they are less likely to take long trips. Flatter curves suggest travelers are less sensitive to travel time and are more willing to make longer trips.

### 6.1.1. Friction Factors

The gamma function was used to develop the friction factor for this model and is shown in Figure 4.

**Equation 6 Friction Factor Equation**

$$\mathbf{F_{ij}^{p} = a * t_{ij}^{b} * \exp(c * t_{ij})}$$

Where:

$F_{ij}^{p}$ = Friction factor for purpose p (HBW, HBO, NHB)

$t_{ij}^{b}$ = travel impedance between zones i and j,

a, b, and c are gamma function scaling factors.

The friction factors were calibrated by adjusting the b and c parameters until the desirable trip length frequency distribution for Home Based Work Travel times was reached. The gamma function allows for a more realistic representation of traveler behavior compared to simpler impedance functions, as it can accommodate different travel sensitivities across trip purposes. Only trips up to 25 minutes were considered with the assumption that 25 minutes was the highest possible travel time between any two points within the metro area. The friction factors in the gravity model were calibrated by adjusting the bbb and ccc parameters in the gamma function until the modeled trip length frequency distribution for Home-Based Work (HBW) travel times aligned with observed data. To ensure accuracy in trip distribution, the desired average trip lengths for other trip purposes were set as proportions of the HBW average trip length, reflecting observed travel behavior differences.

Figure 4 shows the friction factors used in the model plotted against travel time (in minutes). These factors determine the probability of trips occurring over various travel times for different trip purposes. The model applies these friction factors within the gravity model to simulate realistic trip distribution patterns.

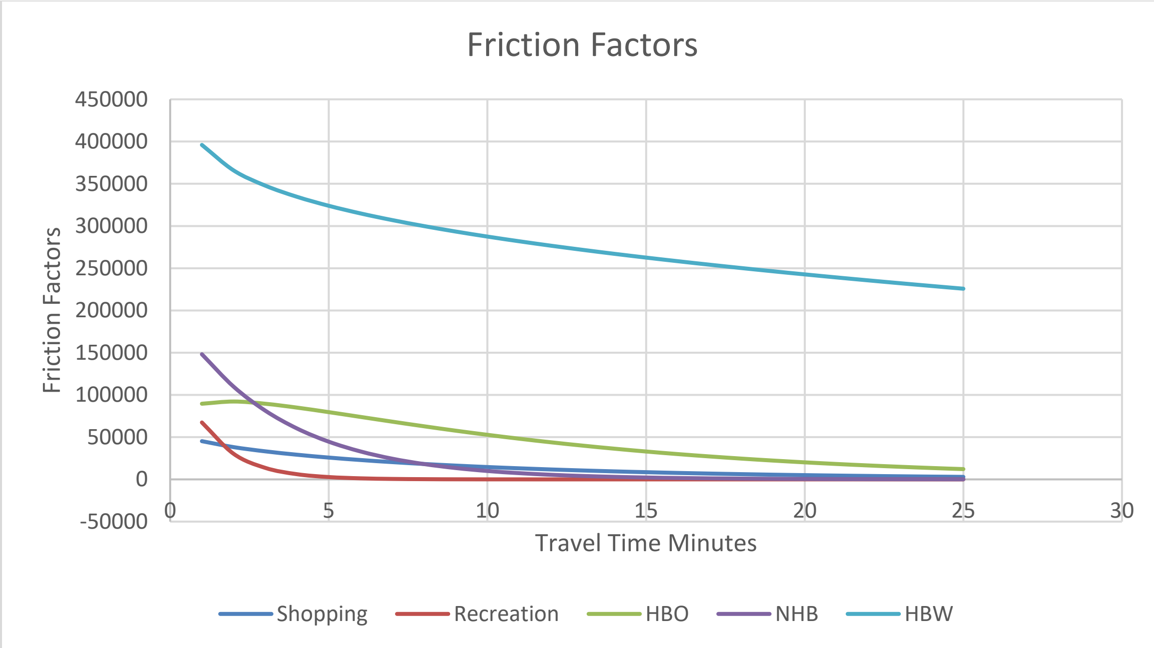


**Figure 4 Friction Factors**

Home-based work (HBW) trips exhibit the highest friction factors across all travel times, indicating that commuters are generally more willing to travel longer distances for work compared to other trip purposes. The gradual decline in friction factors suggests that while most work trips occur within shorter time frames, longer commutes remain common. Home-Based Other (HBO) trips show moderate sensitivity to travel time, meaning that while travelers prefer closer destinations for errands or social activities, they are occasionally willing to travel further. The curve for HBO trips declines more sharply than HBW trips, reinforcing that trip-makers prioritize shorter travel times for discretionary trips.

Non-home-based (NHB) trips begin with relatively high friction factors, which reflects a mix of short business-related and service trips that typically occur within a constrained geographic area. As travel time increases, the friction factor declines steadily, suggesting that while some NHB trips extend over longer distances, most are completed within 10 to 15 minutes. Shopping trips exhibit a steep initial decline in friction factors, indicating a strong preference for nearby retail locations. The lower friction factors at longer travel times suggest that long-distance shopping trips are uncommon, except for specialized stores or major commercial centers.

Recreation trips display the highest travel time sensitivity among all trip categories, with friction factors dropping sharply within the first few minutes. This pattern suggests that most people prefer recreational activities close to home, with only a small portion willing to travel further for special events or destination-based leisure activities such as regional parks or sporting events.

Overall, the friction factor trends confirm that different trip purposes have distinct sensitivities to travel time. Steeper declines indicate a preference for shorter trips, as seen in shopping and recreation trips, while flatter curves suggest that trips are more dispersed over longer distances, as observed with work and non-home-based travel. These calibrated friction factors were refined through an iterative process to ensure that the model accurately reflects observed trip length frequency distributions.

### 6.1.2. Trip Length Frequency Distributions

Figure 5 shows the trip length frequencies for the total HBW, HBS, HBR, HBO, and NHB trips, and for the total Internal-External Trips. For all the trip purposes, there is a sharp increase in the number of trips in 0 to 5 minutes, and a sharp decline in trips occurs between 10 to 15 minutes.

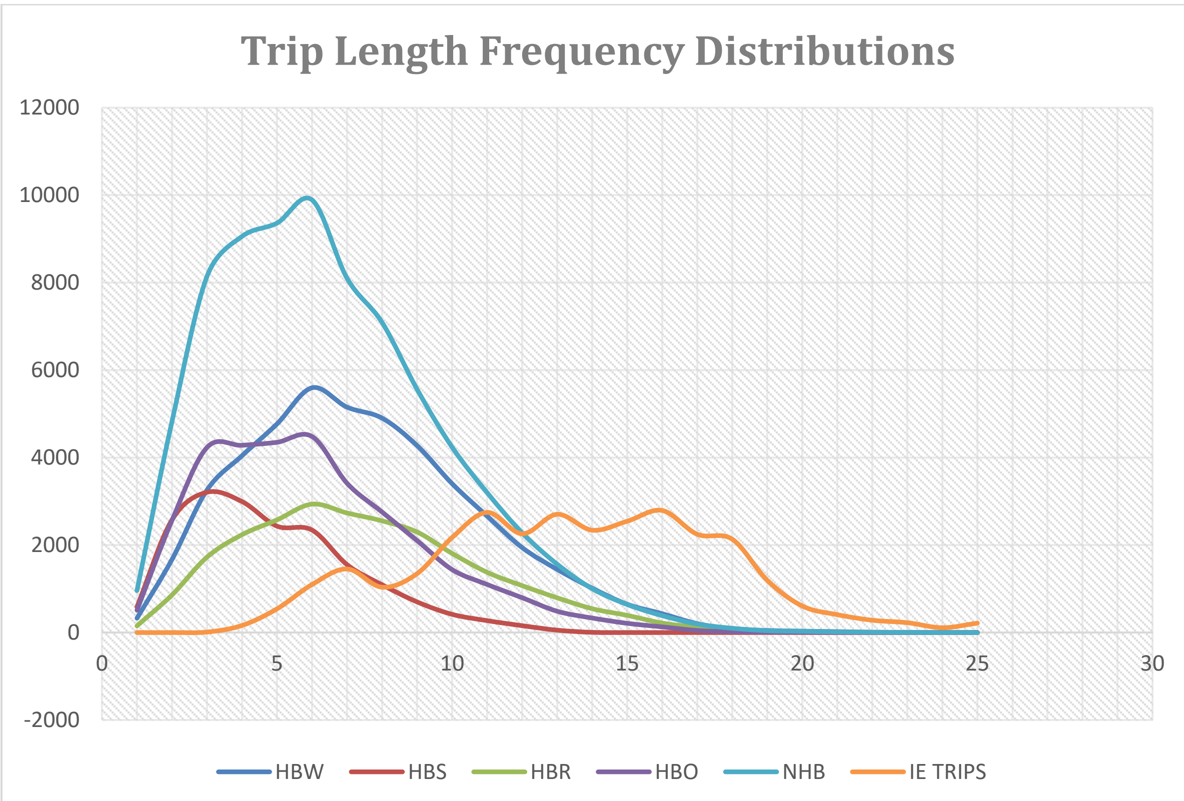


**Figure 5 Trip Length Frequency Distributions by Trip Purposes**

### 6.1.3. Average Trip Length by Trip Purpose

Since observed trip length data was only available for Home-Based Work (HBW) trips, the average trip lengths for other trip purposes were estimated as a percentage of the HBW trip length. This approach ensures consistency in modeling trip distribution while aligning with expected travel behavior patterns.

Table 7 presents the targeted average trip lengths as a percentage of HBW trip length, along with the modeled average trip lengths in minutes for each trip purpose.

**Table 7 Target Average Trip Length and Modeled Average Trip Length**

| Trip Purpose | Target Average Trip Length (% of HBW Trip Length) | Modeled Average Trip Length (minutes) |
|---|---|---|
| **Home-Based Work (HBW)** | 100.00% | 7.78 min |
| **Home-Based School (HBS)** | 62.60% | 4.87 min |
| **Home-Based Recreation (HBR)** | 98.84% | 7.69 min |
| **Home-Based Other (HBO)** | 78.79% | 6.13 min |
| **Non-Home-Based (NHB)** | 85.48% | 6.65 min |

The results indicate that school trips (HBS) have the shortest average travel times, reflecting the tendency for students to attend schools near their homes. Recreational trips (HBR) closely match HBW trips in length, suggesting that some recreation trips, such as visits to parks or entertainment venues, involve travel distances similar to commutes. Non-Home-Based (NHB) and Home-Based Other (HBO) trips fall between these categories, as they include a mix of short and medium-distance trips for various purposes, such as shopping, errands, and business-related travel.

These trip length estimates were carefully calibrated to align with expected travel behavior, ensuring that the model accurately represents trip distribution patterns across different trip purposes.

## 6.2. Modeled ADT Comparison to Observed ADT

Comparing the modeled Average Daily Traffic (ADT) to the observed ADT provides a critical assessment of how well the model replicates real-world traffic conditions. The MPO provided traffic counts for a set of roadway links, which were compared to the model's estimated ADTs. Two levels of comparison were conducted: one by functional classification and another by volume ranges.

### 6.2.1. Observed ADT vs Modeled ADT Comparison by Functional Class

Table 8 shows the comparison of modeled and observed ADTs by functional classification. Overall, the model demonstrates a reasonable performance, replicating over 73% of observed traffic counts. However, because the number of links used for comparison is relatively small, higher deviations are expected, particularly for specific functional classifications where limited sample sizes may contribute to variability.

Table 8 shows the comparison of the modeled and observed ADTs by functional classification. Overall, the model performs reasonably replicating over 73% of observed counts.

**Table 8 Comparison of Modeled and Observed ADTS by Functional Classification**

| Functional Classification | Links | Modeled ADT | Observed ADT | Model/Count % | Typical % Deviation |
|---|---|---|---|---|---|
| **Freeway** | 40 | 262,704 | 238,797 | 10.01 | +/- 10 |
| **Expressway** | 36 | 215,329 | 187,760 | 14.68 | +/- 10 |
| **Principal Arterial** | 56 | 817,204 | 784,095 | 4.22 | +/- 10 |
| **Minor Arterial** | 125 | 761,387 | 717,315 | 6.14 | +/- 15 |
| **Major Collector** | 99 | 197,666 | 209,395 | -5.40 | +/- 30 |
| **Total** | 382 | 2,301,091 | 2,178,805 | 5.61 | |

TDM models typically perform better on higher functional classifications such as freeways and expressways, where traffic flows are more predictable, but show slightly higher deviations for collectors and minor arterials, which tend to have more localized variations in traffic patterns. Given the relatively small sample size of links used for validation, these deviations are expected and do not necessarily indicate fundamental model inaccuracies.

The deviations shown in Table 8 account for variations in traffic volumes caused by real-world conditions that cannot be fully captured by the model, such as signal timing variations, roadway incidents, seasonal fluctuations, and local behavioral factors. Freeways and expressways typically exhibit lower allowable deviations (±10%) because they experience high and stable traffic volumes, making them easier to model with greater precision. Principal arterials also fall within this range as they serve major urban corridors with consistent travel patterns.

For minor arterials, a slightly higher deviation of ±15% is generally acceptable due to the presence of more signalized intersections, variable congestion patterns, and local access points that introduce more variability. Collectors, which serve a mix of local and arterial functions, are subject to greater variation in traffic patterns, leading to a higher allowable deviation of ±25%. Local roads, where trip generation is highly variable and traffic counts are less frequent, can have deviations exceeding ±30%.

### 6.2.2. Modeled Vs Observed Volume by Volume Range Comparison

Table 9 shows the comparison of modeled and Observed ADTs by volume range. The FHWA criterion sets limits to the deviations between observed and modeled ADTs. Comparing the modeled Average Daily Traffic (ADT) to observed traffic counts is a key step in assessing the accuracy and reliability of the travel demand model. The comparison is conducted across different traffic volume ranges, allowing for a more detailed evaluation of how well the model performs in replicating real-world traffic conditions.

Overall, the model achieves a reasonable level of accuracy, with an aggregate deviation of 4.66% across all volume ranges, indicating that it effectively captures regional travel demand patterns.

However, performance varies across different traffic volume categories, which is expected due to the inherent variability in traffic data at different ADT levels.

The model performs well across all volume ranges, with deviations remaining within the acceptable limits for each category. The highest accuracy is observed in the mid-range and high-volume categories, indicating that the trip distribution and assignment processes are well-calibrated for arterials and highways. In contrast, the greatest deviation occurs in the low-volume road category (ADT 0-1,000), which is expected due to the inherent variability in traffic patterns and data collection challenges associated with these roads. Additionally, the slight underestimation in the highest ADT category suggests that minor refinements in network capacity or trip assignment could enhance accuracy for major corridors and freeways.

Overall, the model demonstrates a strong ability to replicate real-world traffic conditions, with a total deviation of 4.66% across all ADT categories. This level of accuracy supports the model's reliability for transportation planning and policy decisions. Future refinements could focus on improving precision in low-volume road classifications while maintaining the strong performance observed in higher-volume categories.

**Table 9 Comparison of Modeled and Observed ADT by Volume Range**

| ADT Range | Links | Model ADT | Count ADT | Model/Count % | Acceptable % |
|---|---|---|---|---|---|
| **ADT 0-1000** | 45 | 71,568 | 28,680 | 149.4 | 200 |
| **1,001 TO 2,500** | 68 | 149,204 | 120,433 | 23.89 | 47 |
| **2,501 TO 5,000** | 106 | 384,568 | 375,590 | 2.39 | 36 |
| **5,000 TO 10,000** | 120 | 886,866 | 839,997 | 5.58 | 29 |
| **>10000** | 43 | 788,046 | 814,105 | -3.20 | 15 |
| **Total** | 382 | 2,280,253 | 2,178,805 | 4.66 | |

## 6.3. Scatter Plots, R Squares of Model, and Observed Traffic

Scatter plots comparing modeled traffic volumes to observed traffic counts are an effective way to assess the model's overall fit and accuracy. Figure 6 shows the scatter plot of modeled traffic volumes versus observed counts. The plot suggests that the amount of error in the modeled volumes is proportional to the observed traffic counts, which is an indication of a good fit between the model and real-world traffic conditions.

A key statistical measure displayed in the figure is the R-squared ($R^2$) value, also known as the coefficient of determination. This metric quantifies the proportion of variation in observed traffic counts that can be explained by the modeled traffic volumes. A higher $R^2$ value indicates a stronger relationship between the two variables.

In this case, the modeled $R^2$ value of 0.80 suggests a strong linear correlation between modeled and observed traffic counts, meaning that the model can capture a significant portion of the variation in actual traffic patterns. While some discrepancies are expected due to localized variations in traffic flow, data collection limitations, or minor calibration adjustments, the overall trend suggests that the model performs well in replicating observed traffic volumes.

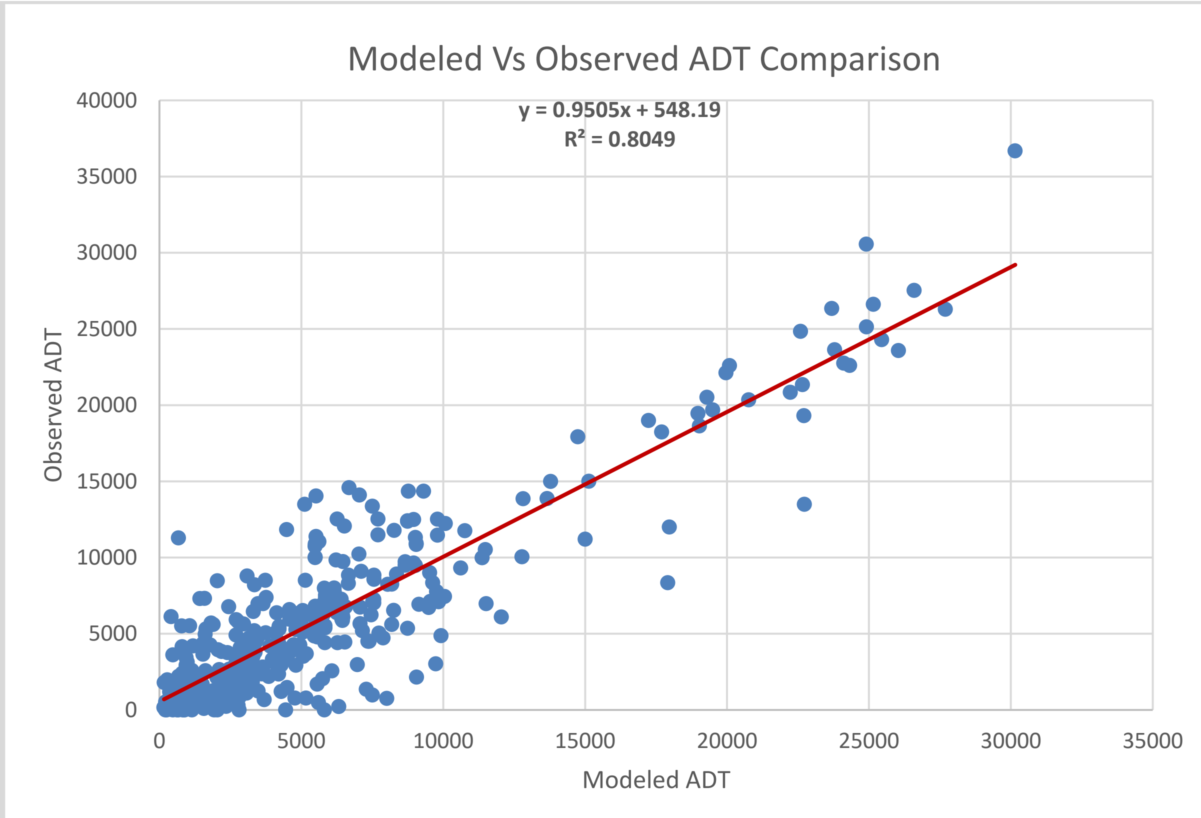


**Figure 6 Scatter Plot of Modeled and Observed ADTS**

# 7. CONCLUSIONS

This document details the development, calibration, and validation of the Central Dakota MPO 2022 base-year Travel Demand Model (TDM). The model follows the standard four-step modeling process, consisting of trip generation, trip distribution, mode choice (if applicable), and trip assignment, to estimate travel patterns within the MPO region.

The trip generation step establishes the number of trips produced and attracted to each Traffic Analysis Zone (TAZ) using socioeconomic data and calibrated trip production and attraction rates. The trip distribution step applies a gravity model with calibrated friction factors to allocate trips between origins and destinations, ensuring that modeled trip length distributions align with observed travel behavior. The trip assignment step assigns these trips to the transportation network using a User Equilibrium (UE) approach, where travelers select routes that minimize their perceived travel time. The assignment process considers volume-delay functions, roadway capacities, and congestion effects, leading to realistic traffic flow estimations.

The model was successfully calibrated and validated using traffic count data provided by the MPO. A comparison of modeled and observed traffic volumes indicates that the model performs within typically accepted deviation limits across different functional classifications and volume ranges. The scatter plot analysis confirms a strong correlation ($R^2 = 0.80$) between modeled and observed ADTs, demonstrating the model's ability to replicate real-world travel patterns accurately.

With this level of accuracy, the Central Dakota MPO TDM serves as a reliable tool for forecasting future traffic conditions, evaluating potential infrastructure improvements, and assessing the impacts of policy changes on the regional transportation system. While future refinements may improve model precision—particularly on lower-volume roads—the model provides a solid foundation for data-driven transportation planning and decision-making.