NDSU UPPER GREAT PLAINS TRANSPORTATION INSTITUTE

ATAC ADVANCED TRAFFIC ANALYSIS CENTER

GRAND FORKS EAST GRAND FORKS 2021 TRAVEL DEMAND MODEL UPDATE

EXECUTIVE SUMMARY

to the Grand Forks East Grand Forks MPO

APRIL 2023

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TABLE OF CONTENTS

1. Introduction 1

2. Trip Generation 3

3. Trip Distribution and Modal Split 4

4. Traffic Assignment 6

4.1. Traffic Count Comparisons 6
4.2. Comparison of Traffic Counts to Model ADT by Volume Range 7
4.3. Comparison of Traffic Counts to Model ADT by Functional Classification 8

LIST OF FIGURES

Figure 1 GF-EGF TDM Calibration Flow Chart 1
Figure 2 Comparison of Observed Vs Model Trip Length Frequency Distributions 5
Figure 3 Comparison of Model and Observed ADT 7

LIST OF TABLES

Table 1 Summary of Trip Generations Compared to 2015 Model Output 3
Table 2 Comparison of Model and Observed Screenline Counts 4
Table 3 Comparison of Model ADT to Observed ADT by Volume Range 8
Table 4 Comparison of Model and Observed ADTs by Functional Class 9

1. INTRODUCTION

The Grand Forks East Grand Forks MPO's (The Forks MPO) Travel Demand Model (TDM) is updated every five years to reflect new ground truths/data and the advancements in the state-of-the-art in transportation modeling techniques and methods. The current update reflects the base year 2021 data. The model is a four-step TDM including trip generations, trip distributions, modal split, and trip assignment. The update process involves calibrating the model input parameters and validating the model output with ground truths. The model calibration is a cyclical process as shown in Figure 1.

This executive summary provides an overview of the travel demand model calibration and validation process and results for The Forks MPO. The travel demand model is an essential tool for transportation planning, and accurate calibration and validation are crucial for ensuring that the model reflects the travel patterns and behavior of the population. The calibration process involves adjusting the model parameters to achieve the best fit between the modeled and observed data, while the validation process involves comparing the modeled output with the observed data to ensure that the model accurately represents the travel patterns and behavior of the population.

In this summary, we present the results of the calibration and validation process for The Forks MPO travel demand model. We use several types of output to validate the model, including screenline counts, link counts, origin-destination matrices, mode and route choice, and parking demand. We also present the results of an analysis of volume ranges to identify any variations in model performance.

Overall, the results indicate that the travel demand model is performing well in representing the observed traffic volumes and travel patterns, with some exceptions for mid-range volume categories. The results of the calibration and validation process will help transportation planners to make informed decisions and improve the accuracy of future travel demand modeling efforts for The Forks MPO.

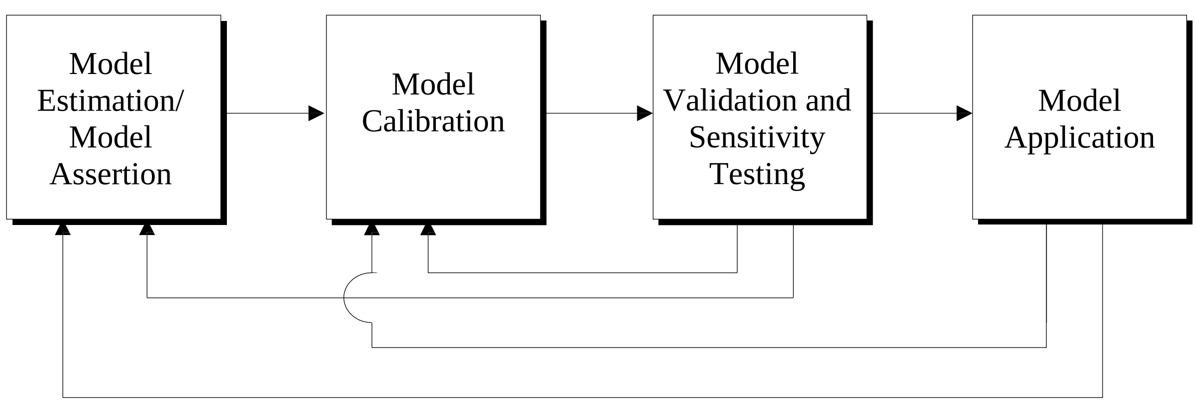

Figure 1 GF-EGF TDM Calibration Flow Chart

This document is divided into four sections that describe the travel demand model calibration and validation process. Chapter 1 focuses on the calibration of the trip generation component of the model. This Chapter explains how the number of trips generated by different zones in the study area was estimated using the model, and how the model parameters were adjusted to achieve the best fit between the modeled and observed data.

Chapter 2 describes the calibration of the trip distribution and modal split components of the model. This Chapter explains how the flow of trips between different zones and the proportion of trips made using different modes of transportation were estimated using the model, and how the model parameters were adjusted to achieve the best fit between the modeled and observed data.

Chapter 3 focuses on the calibration and validation of the trip assignment component of the model. This Chapter explains how trips were assigned to specific routes in the transportation network using the model, and how the model parameters were adjusted to achieve the best fit between the modeled and observed traffic volumes on specific links. Most of the traffic data collected is observed volumes, VMT, and trip length frequencies which are output from the trip assignment step. The overall validation results are discussed in this chapter.

Chapter 4 summarizes the overall results and discusses the next steps.

2. TRIP GENERATION

The observed traffic counts for the year 2021 were compared to those of 2015, and the results showed that the counts were generally lower than in 2015. This trend was likely due to the impact of the COVID-19 pandemic on travel patterns and behavior. To account for these changes, trip generation equations were adjusted using data from Streetlight Inc in the Fargo Moorhead area and the Bismarck Mandan MPO area, which showed a decrease of about 14% compared to 2017 data. After adjusting the trip generation rates, Table 1 shows the total trips that were generated. The number of trips generated for the year 2021 was reasonable, however, the research on whether trips will rebound to pre-COVID levels is still uncertain. Some studies suggest that trips will return to pre-pandemic levels or even exceed them, while others indicate that they will not. Therefore, for future scenarios, it will be prudent to test a range of trip generation equations that cover the potential rebounding of trips to pre-COVID levels. Table 1 shows the total trips generated during peak hours, off-peak hours, and the overall total trips for both 2015 and 2021, with percentage differences indicated. The data shows a decrease in traffic volumes for all categories, with a 2% decrease during peak AM hours, a 9% decrease during peak PM hours, a 15% decrease during off-peak hours, and an overall 12% decrease in total traffic volumes. Based on the adjusted trip generation equations and the observed traffic data, we believe that the trips were reasonably calibrated and reflect the current travel patterns and behavior of the population in the study area.

Table 1 Summary of Trip Generations Compared to 2015 Model Output

Period	2015	2021	% Difference
Peak AM	46,037	45,192	**-2%**
Peak PM	55,539	51,173	**-9%**
Off Peak	197,680	171,809	**-15%**
Total	**299,256**	**268,174**	**-12%**

3. TRIP DISTRIBUTION AND MODAL SPLIT

For the trip distribution and modal split component of the model, we used vehicular and transit modes. The transit data was provided by the MPO for each of the main transit lines, which was supplemented with General Transit Feed Specification (GTFS) data. The overall model showed a reasonable representation of the transit mode. For the vehicular mode, we evaluated how well the model was distributing trips across screenlines since we did not have any observed Origin-Destination (OD) data for 2021 although we had pre-COVID data. Screenlines are geographic lines on a road network that divide an area into smaller sections for analysis. They are often used in transportation planning to evaluate traffic flow and movement across a particular area. These lines can be man-made barriers such as rivers, highways, and railroads, or they can be natural features like mountains or forests. Since travel patterns and behavior can be significantly influenced by these barriers, screenlines are an effective way to analyze how well a travel demand model is distributing trips across an area. We adjusted the trip distribution parameters to reflect the screenline counts as closely as possible while keeping in mind that some variations are acceptable in any model.

We primarily used three screenlines for our analysis: Red River, I-94, and BNSF Railroad. Table 1 shows the modeled Average Daily Traffic (ADT) volumes and the observed Annual Average Daily Traffic (AADT) volumes, along with the percentage difference for each screenline. The Red River screenline showed an overall difference of 3%, while the I-94 screenline showed an overall difference of 10%. The BNSF Rail Road screenline, on the other hand, showed an overall difference of -7%. The results showed that the modeled volumes generally matched well with the observed volumes for each screenline, indicating that our model was effectively distributing trips across these barriers. Acceptable limits for volumes greater than 50,000 are typically less than a 10% deviation from traffic counts.

Table 2 Comparison of Model and Observed Screenline Counts

Screenline	Modeled ADT	AADT	% Difference
Red River	34,435	33,297	3.3%
BNSF Rail Road	80,684	86,603	-7.3%
I-94	67,763	61,001	10.0%

Another output used to validate the travel demand model is the trip length frequency distribution, which is the distribution of the length of trips taken by travelers in a region. The distribution of trip lengths is an important input for the gravity model used in trip distribution, which calculates the number of trips between zones based on the attractiveness of each zone and the cost of travel between them. The trip length frequency distribution is, therefore, an important measure of the accuracy of the travel demand model in simulating travel behavior, and is often used to validate and calibrate the model. We evaluated the observed vs trip length frequency data between the model and observed data from the ACS survey, which provides information on the distribution of trip lengths for all modes of transportation. The table above shows the comparison between the observed and modeled trip length frequencies, and while there are some differences, we can conclude that the model is successfully validated. It is important to note that the observed data from the ACS survey was for the entire metropolitan statistical area, whereas our data was for only the MPO boundary, so some differences were expected. However, the patterns of trip length frequencies in the modeled data follow what we expect to see using the gravity model for trip distribution.

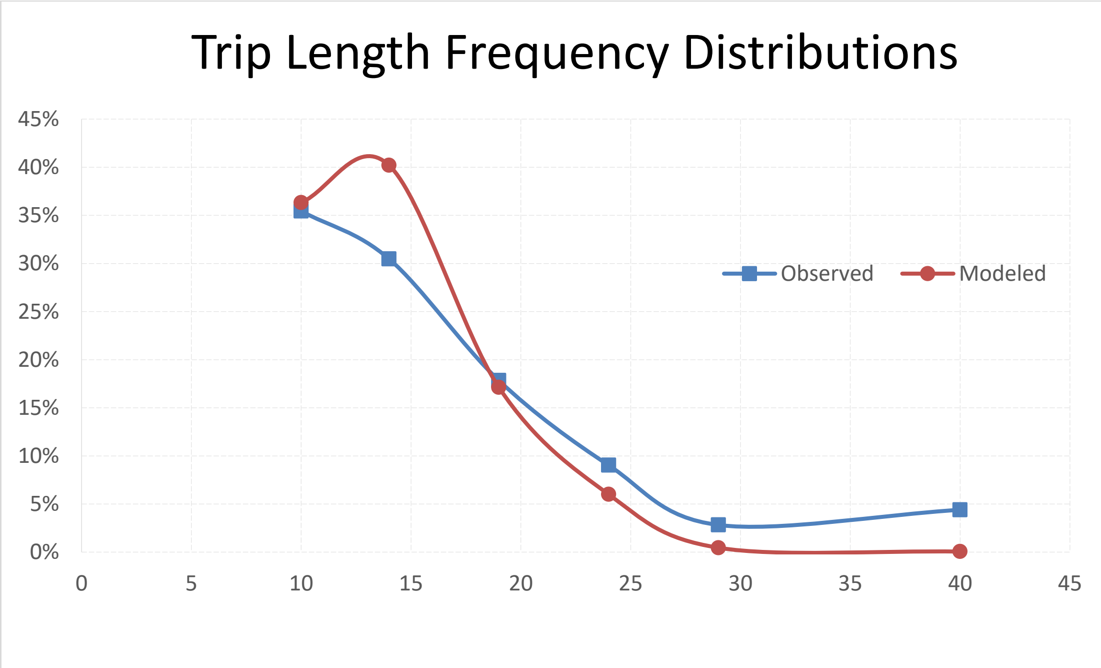

Figure 2 Comparison of Observed Vs Model Trip Length Frequency Distributions

Based on the provided trip length-frequency data, a chi-squared goodness-of-fit statistical test was conducted to compare the observed and modeled trip length frequency distributions. The null hypothesis for this test is that the observed and modeled distributions are the same, while the alternative hypothesis is that they are different. A p-value less than 0.05 would indicate that there is strong evidence to reject the null hypothesis and conclude that the distributions are different. The results of the chi-squared test are as follows:

Chi-squared statistic: 1.3227 Degrees of freedom: 5 p-value: 0.9327

The p-value is greater than 0.05, indicating that there is no significant evidence to reject the null hypothesis. Therefore, we can conclude that the observed and modeled distributions are similar.

In addition to the chi-squared test, we can also compute some measures of similarity between the two distributions. One commonly used measure is the Kolmogorov-Smirnov statistic, which compares the cumulative distribution functions of the two samples. The Kolmogorov-Smirnov statistic for this data is 0.1903, which is relatively small compared to the maximum difference of 0.2608 between the two distributions. This also suggests that the observed and modeled distributions are similar.

4. TRAFFIC ASSIGNMENT

For the traffic assignment step, we utilized the Bureau of Public Roads (BPR) formulation to calculate traffic impedances. These impedances were then adjusted to reflect the observed travel times on links based on their functional classes. To obtain travel time data, we used online sources and obtained travel times between several points on the network using Google Maps. These were then used to adjust the BPR parameters to closely reflect the observed traffic. The functional class adjustments were made to ensure that travel times reflected the appropriate travel speeds for different types of roads. For example, travel times on arterials were adjusted to reflect the higher speeds and free flow conditions, while travel times on local roads were adjusted to reflect lower speeds and more congestion. Overall, these adjustments helped to improve the accuracy of the traffic assignment results and ensure that the modeled traffic volumes were distributed appropriately across the road network. For traffic assignment validation, the model was compared to overall traffic counts, traffic counts by volume range, traffic counts by functional classification, and vehicle miles traveled. These results are discussed next.

4.1. Traffic Count Comparisons

Comparing observed and modeled volumes from the assignment step is an essential part of validating a travel demand model. The assignment step is where the trips generated in the previous steps of the model are assigned to the available transportation network. The objective of this step is to estimate the number of trips that will use each road segment, considering the available modes of transportation, the travel time, and other factors. By comparing the modeled volumes with the observed volumes, we can check how well the model is performing.

Several criteria can be used to assess the model's accuracy. One common criterion is the coefficient of determination (R-squared), which measures the proportion of the variation in the observed data that is explained by the model. Another common criterion is the root-mean-square error (RMSE), which measures the difference between the modeled and observed volumes. A low RMSE indicates a better fit between the modeled and observed volumes.

Figure 3, shows the comparison of the model and observed ADTs. It shows that the observed volumes and modeled volumes are close in some cases, but some variations occur and are expected. The R-squared value R-square value is 0.936, which indicates that the model closely fits the observed volumes. This value indicates that the model is performing moderately well and is successfully validated.

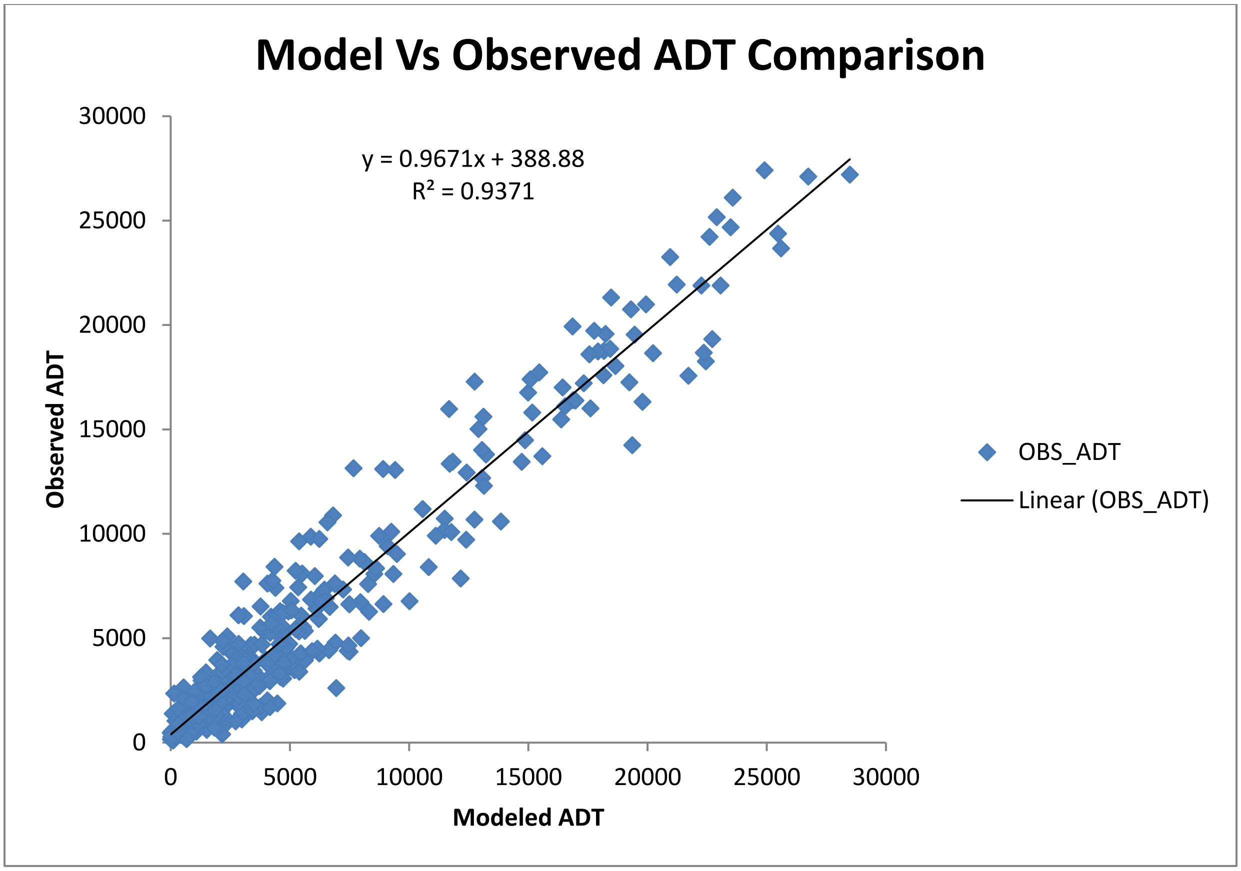

Figure 3 Comparison of Model and Observed ADT

4.2. Comparison of Traffic Counts to Model ADT by Volume Range

The model validation process involved examining the model's predicted traffic volumes against observed traffic volumes within specific volume ranges. These volume ranges represented average daily traffic (ADT) levels, which were key indicators of roadway usage and congestion. Comparing the model's performance by volume range was crucial in identifying whether different volume ranges were impacting the model's accuracy and precision, allowing for the implementation of corrective measures as needed. By analyzing the model's performance in predicting traffic volumes within each volume range, insights were gained into its strengths and weaknesses, and areas for improvement were identified. This approach facilitated a targeted evaluation of the model, ensuring that any necessary adjustments could be made to enhance its predictive capabilities across all volume ranges.

Table 1 shows a detailed comparison of the model's predicted traffic volumes with the observed data across six distinct volume ranges. The model's performance was evaluated by analyzing the number of links within, above, or below the expected volume range for each ADT category. Additionally, the percentage of links within the expected volume range and the root mean square error (RMSE) for each volume range were discussed, providing a comprehensive assessment of the model's overall accuracy and precision.

Table 3 Comparison of Model ADT to Observed ADT by Volume Range

Volume Range	#Above	#Within	#Below	%Within	RMSE
ADT>25,000	0	5	0	100%	0.075
25,000-10,000	9	48	9	73%	0.156
10,000-5,000	7	45	22	61%	0.271
5,000-2,500	6	84	8	86%	0.392
2,500-1,000	9	88	0	91%	0.602
ADT<1000	6	41	0	87%	1.043

- For the volume range with average daily traffic (ADT) greater than 25,000, all five links (100%) were within the expected volume range, indicating an excellent fit with an RMSE of 0.0750.
- In the 25,000 to 10,000 ADT volume range, 48 out of 66 links (72.73%) were within the expected range, while nine links were above and nine were below. The RMSE for this range is 0.1569, suggesting a relatively good model fit.
- The 10,000 to 5,000 ADT volume range had 45 out of 74 links (60.81%) within the expected range, with seven links above and 22 below the range. This volume range had an RMSE of 0.2719, indicating a moderate model fit.
- For the 5,000 to 2,500 ADT volume range, 84 out of 98 links (85.71%) were within the expected range, while six links were above and eight were below. The RMSE for this range is 0.3924, indicating a good model fit.
- The 2,500 to 1,000 ADT volume range showed the best model fit, with 88 out of 97 links (90.72%) within the expected range and nine links above the range. No links were below the range in this category. The RMSE for this range is 0.6027.
- For the ADT below 1,000 volume range, 41 out of 47 links (87.23%) were within the expected range, while six links were above the range. No links were below the range. The RMSE for this volume range is 1.0432.

In summary, the total number of links within the expected volume range is 311 out of 387 (80.36%), showing that the travel demand model provides a reasonably good fit for the observed data.

4.3. Comparison of Traffic Counts to Model ADT by Functional Classification

In addition to comparing the modeled volumes by volume range, the travel demand model's performance was also evaluated by functional class. This approach was essential in identifying if a particular functional class had a significantly higher error, enabling the adjustment of model input parameters to address the issue and improve the model's accuracy for that specific functional class. The results of the comparison by functional class are summarized in Table 4.

Table 4 Comparison of Model and Observed ADTs by Functional Class

Functional Class	#Above	#Within	#Below	%Within	RMSE
Freeway	0	10	0	100%	0.1203
Majors	12	62	9	75%	0.1865
Minors	11	106	15	80%	0.6131
Rural	0	4	0	100%	0.531
Collector	12	110	15	80%	0.5812
Local	2	19	0	90%	0.603

- For the freeway functional class, all ten links (100%) were within the expected range, indicating an excellent model fit with an RMSE of 0.1203.
- Major arterials had 62 out of 83 links (74.70%) within the expected range, with 12 links above and nine below the range. The RMSE for this functional class was 0.1865, suggesting a relatively good model fit.
- In the case of minor arterials, 106 out of 132 links (80.30%) were within the expected range, while 11 links were above and 15 were below. The RMSE for this functional class was 0.6131, indicating a moderate model fit.
- For rural paved roads, all four links (100%) were within the expected range, displaying an excellent fit with an RMSE of 0.5310.
- Collectors had 110 out of 137 links (80.29%) within the expected range, with 12 links above and 15 below the range. The RMSE for this functional class was 0.5812, suggesting a good model fit.
- Lastly, local roads had 19 out of 21 links (90.48%) within the expected range, with two links above the range. No links were below the range for this functional class, and the RMSE was 0.6030, indicating a strong model fit.

Based on the results of the comparisons by volume range and functional class, the travel demand model was successfully validated. The model demonstrated a reasonably good fit for the observed data across various volume ranges and functional classes, with the majority of links within the expected range and relatively low root mean square errors. The targeted evaluation approach allowed for the identification of specific areas for improvement, enabling the adjustment of model input parameters as needed to enhance the model's predictive capabilities across all volume ranges and functional classes. Given these results, we believe that the travel demand model has been successfully validated and is capable of effectively informing transportation planning and policy decisions.