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Performance evaluation of travel demand forecasting models for transportation network analysis

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Abstract

This paper presented a performance evaluation of travel demand forecasting techniques on transportation networks in Upper Northern Provincial Cluster 2, Thailand. The study compared multiple regression analysis and four-step sequential decision models. The findings revealed that the four-step sequential decision model forecasted person-trip generation in the study area to be 346,506, 373,422, 404,356, and 440,132 person-trips/day for the years 2029, 2034, 2039, and 2044, respectively. In comparison, the multiple regression model predicted approximately 320,245, 328,678, 338,123, and 349,567 person-trips/day for the same years, showing differences of 8.20%, 13.61%, 19.59%, and 25.91%, respectively. This variation can be attributed to the four-step sequential decision model's superior capability in comprehensively considering the impacts of future infrastructure development projects in the area compared to the multiple regression model. While both models forecast total person-trip generation, the four-step model additionally provides spatial distribution, modal allocation, and network assignment of these trips, enabling detailed analysis of traffic volumes on specific corridors. However, when evaluating model development convenience and time requirements, the multiple regression analysis approach offers faster problem-solving capabilities due to its more straightforward development process, while providing reasonably accurate forecasts of total person-trips.

Keywords: Travel demand forecasting, Multiple regression analysis, Four-Step sequential decision model, Performance evaluation

1. Introduction

Transportation demand forecasting is a critical component in infrastructure planning and policy development, serving as a fundamental tool for predicting future mobility patterns and facility requirements. Various analytical approaches have been developed, ranging from experience-based forecasting methodologies [1, 2] to evidence-based analytical frameworks [3, 4] and sophisticated statistical modeling utilizing historical data [5, 6].

In transportation planning, demand forecasting involves predicting passenger and freight movements across various modes of transportation. This includes estimating vehicular traffic volume [7, 8], projecting railway ridership [9], analyzing aviation passenger demand [10, 11], and forecasting maritime transport volume [12, 13]. These predictions integrate multiple variables, including socioeconomic indicators, land use patterns, trip generation rates, and generalized travel costs [14, 15], to develop comprehensive demand models that accurately represent travel behaviors and project future scenarios.

The complexity of modern transportation systems necessitates sophisticated modeling approaches that can capture the intricate relationships between travel demand and its determining factors. Multiple regression analysis has emerged as a widely adopted method due to its ability to quantify the relationships between dependent and independent variables while maintaining computational efficiency [16, 17]. Concurrently, the four-step sequential model remains a cornerstone in transportation planning, offering a comprehensive framework that addresses trip generation, distribution, modal choice, and network assignment through discrete yet interconnected stages [18, 19].

This research presents a comparative assessment of two prominent methodologies - multiple regression analysis and the four-step sequential model - in the context of Thailand's Upper Northern Provincial Cluster 2. The study aims to evaluate the relative performance, advantages, and limitations of each approach in forecasting travel demand patterns. By analyzing their predictive accuracy, computational requirements, and ability to incorporate the impacts of infrastructure development, this research provides

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transportation planners with empirical evidence for selecting appropriate modeling approaches based on specific planning contexts and resource constraints.

Despite the widespread application of both methodologies in transportation planning, a significant research gap exists in their comparative evaluation within rapidly developing regions. Few studies have directly compared their effectiveness under conditions of accelerated infrastructure development, particularly in Southeast Asia. This gap limits transportation planners' ability to make informed methodological choices when allocating limited resources. This study addresses this need by systematically comparing these approaches in Thailand's Upper Northern Provincial Cluster 2, a region experiencing substantial transportation infrastructure development. By quantifying the relative advantages and limitations of each method under comparable conditions, this research provides practical guidance for selecting a methodology based on planning objectives, data availability, and resource constraints.

This study is significant because it systematically compares traditional and contemporary forecasting methodologies within a real-world planning context. The findings will contribute to a broader understanding of model selection criteria in transportation planning, particularly in rapidly developing regions where infrastructure investment decisions carry significant long-term implications for mobility and economic development.

2. Methodology

This research presents a comprehensive evaluation of travel demand forecasting methodologies for transportation network analysis, comparing the statistical approach of multiple regression analysis with the conventional four-step transportation model in Thailand's Upper Northern Provincial Cluster 2. The methodological framework for assessing the comparative performance of these demand forecasting techniques within the context of transportation networks is illustrated in Figure 1.

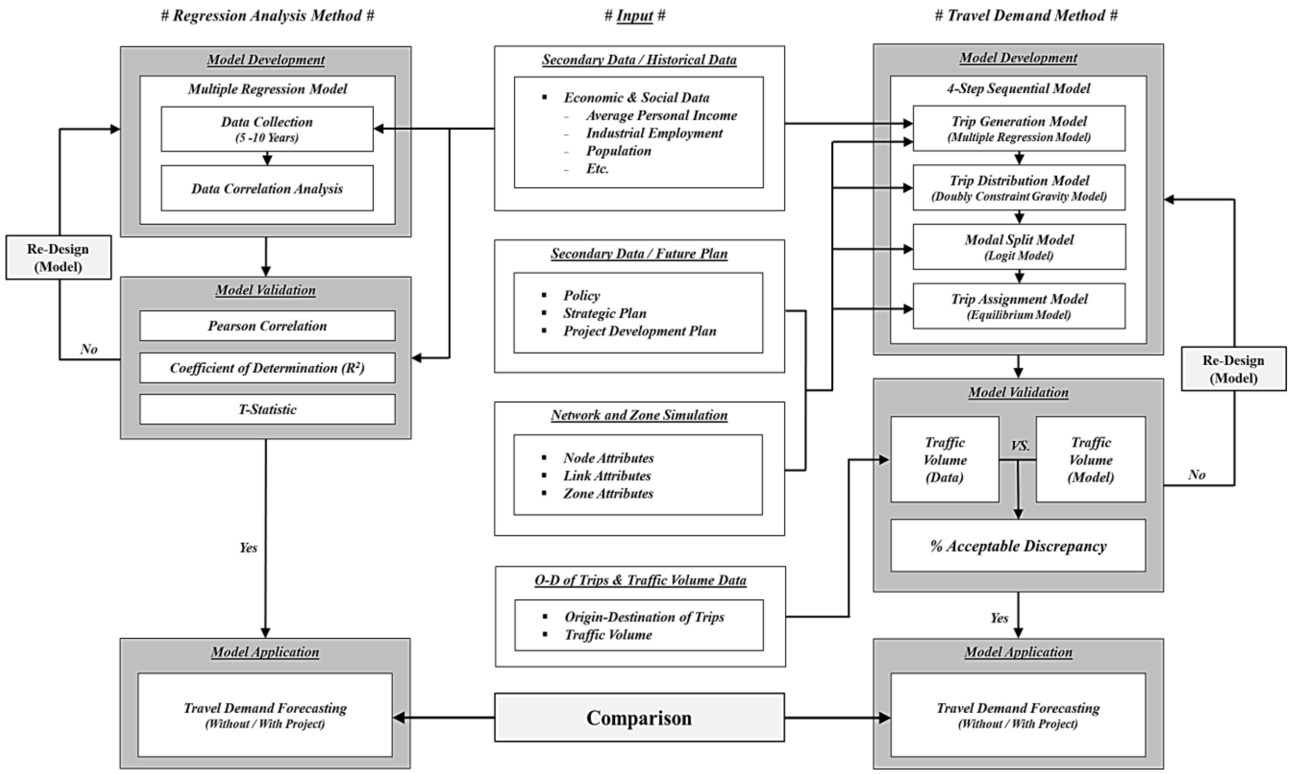


Figure 1 Methodological Framework for Travel Demand Forecasting Assessment

2.1 Definitions and terminology

Determining key terminology used throughout this study is crucial for ensuring clarity and precision in the methodological approach and the interpretation of results.

"Person-trips": In this research, our primary dependent variable is "person-trips," defined as the movement of one person from an origin to a destination for any purpose. The study analyzes explicitly total daily person-trips (trips/day) and peak hour person-trips (trips/hour) within and between the traffic analysis zones (TAZs) of Upper Northern Provincial Cluster 2. This measure represents travel demand in its fundamental form—the need for individuals to move between specific locations.

“Traffic volumes”: While person-trips represent the demand for movement, traffic volumes represent the flow of vehicles on specific network links (roads). In the four-step model, traffic volumes are derived through the assignment process (step four), which allocates person-trips (converted to vehicle-trips through mode choice) to specific routes in the transportation network. Therefore, the relationship between person-trips and traffic volumes is sequential and causal, with person-trips serving as inputs to the process that ultimately generates traffic volume estimates.

The distinction between these terms is critical to understanding our methodology. The multiple regression analysis model directly forecasts the total number of person trips generated within the study area based on socioeconomic factors. In contrast, the four-step sequential decision model first generates person trips (step 1), distributes them between origins and destinations (step 2), allocates them to transportation modes (step 3), and finally assigns vehicle trips to the road network to produce traffic volumes (step 4).

This study utilizes all four steps of the sequential modeling process. Our research objectives extend beyond merely forecasting total trip generation to understanding how these trips will be distributed across the network, which modes will be used, and how specific infrastructure projects will impact traffic volumes on particular corridors. This comprehensive approach enables a more detailed assessment of the impacts of infrastructure development, a key objective of this comparative evaluation.

2.2 Data collection for model development

The study collected comprehensive data from Thai government agencies [20], including travel and transport data from the Office of Transport and Traffic Policy and Planning (OTP) for origin-destination patterns [21], Annual Average Daily Traffic (AADT) from the Department of Highways [22], Vehicle Registration Statistics from the Department of Land Transport [23] and freight transport statistics from the OTP. [24]. Infrastructure data included current road networks, transport systems, and future development plans [25]. Socioeconomic data encompassed population statistics [26], employment figures [27], economic indicators [28], and land use information from relevant government departments [29].

2.3 Model development

Multiple Regression Analysis development analyzes relationships between independent variables (Population, employment, income, and land use) and the dependent variable (number of trips) in the study area, using statistical principles to create optimal linear relationship equations for forecasting future trip numbers based on changes in the specified independent variables [16, 17]. Four-step sequential decision models development follows transportation engineering principles from the National Model (NAM) of the Office of Transportation and Traffic Policy and Planning [30]. The model comprises four sequential sub-models: Trip Generation using regression analysis, Trip Distribution using the doubly constrained gravity method, Mode Choice using utility analysis or the logit model, and Trip Assignment using the user equilibrium method [18, 19].

2.4 Model calibration

2.4.1 Multiple regression model calibration process

The multiple regression model calibration followed a four-stage approach. First, the coefficient of determination (R-squared) was assessed with a minimum threshold of 0.85, achieving a final value of 0.895 after parameter refinement. Second, validation compared predicted versus observed travel volumes for 2024, yielding a root mean square error (RMSE) of 8.7%, below the 10% acceptance criterion. Third, statistical significance testing confirmed all variables were significant at a 95% confidence level ($p < 0.05$), with p-values ranging from 0.027 to 0.042. Finally, a sensitivity analysis verified the logical model's responses to demographic and economic changes. Key assumptions included linear relationships between variables, a normal distribution of standard errors, and independent observations.

2.4.2 Four-Step sequential decision model calibration process

The four-step model calibration addressed each component sequentially. The trip generation model was calibrated using household and land use data, achieving an R-squared of 0.87 and RMSE of 9.3%, meeting acceptance criteria ($R^2 > 0.80$, RMSE < 12%). Trip distribution calibration optimized gravity model parameters to match observed trip length distributions, achieving a correlation coefficient of 0.91. Mode choice calibration estimated utility function coefficients using revealed preference data, with goodness-of-fit measured by rho-squared ($\rho^2 = 0.38$). Trip assignment calibration compared modeled traffic with observed counts at 68 network locations, adjusting parameters until meeting acceptable error margins according to road types: arterial roads (±15%), collector roads, frontage roads, and one-way roads (±25%), following the FSUTMS-Cube Framework Phase II (2008) standards, as shown in Table 1 [31]. The calibrated model yielded a GEH statistic of 4.2 and an R-squared value of 0.92, indicating a strong correlation between the observed and modeled volumes.

Both calibration processes used the 2024 dataset as the base year, with 70% allocated for model development and 30% for validation, ensuring a reliable foundation for future predictions.

Table 1 Acceptable Error Margins in Trip Assignment

Road Type	Acceptable Error (%)
Arterial	±15%
Collector	±25%
Frontage Road	±25%
One-Way	±25%

2.5 Model application

The Multiple Regression Analysis application utilizes the developed relationship equations to forecast future travel demand by considering changes in independent variables, including Population, employment, income, and land use, for travel demand prediction from 2024 to 2044. The Four-Step Sequential Decision Model application utilizes a calibrated model to forecast future travel demand by examining the effects of major transportation infrastructure development projects in the study area. The analysis was conducted in two scenarios: One without the Project and one with the Project, according to the development plan from 2024 to 2044, as shown in Table 2.

Table 2 Future Development Projects Used to Update Network Model Database

No.	Project Name	Year				
		2024	2029	2034	2039	2044
1	Den Chai-Chiang Rai-Chiang Khong Double-Track Railway Project		●	●	●	●
2	Motorway-Rail Integration Project (MR-MAP) Route 1: Chiang Rai - Narathiwat (MR1)				●	●

2.6 Comparison of forecasting results between two models

The comparison of forecasting results between the two models was conducted by analyzing the differences in future travel demand predictions between the multiple regression analysis model and the four-step sequential decision model from 2024 to 2044. The evaluation considered multiple aspects, including forecast accuracy, model development complexity, implementation timeframe, and application constraints of each model to assess their suitability for future transportation planning purposes.

3. Results

3.1 Development of multiple regression analysis model

3.1.1 Preliminary analysis results

The correlation analysis of factors affecting travel demand in Upper Northern Provincial Cluster 2, comprising four provinces (Chiang Rai, Phayao, Phrae, and Nan), revealed that trip generation (TRIP) exhibited robust positive correlations with Annual Average Daily Traffic (AADT) and registered vehicles (VEH), with correlation coefficients of 0.98 and 0.96 respectively, and statistical significance levels of 0.09 and 0.12 respectively. This was followed by correlations with Population (POP) and employment (EMP), showing correlation coefficients of 0.93 and 0.89, respectively. Meanwhile, land use (LAND) demonstrated low correlations with all other variables, with correlation coefficients ranging from 0.18 to 0.35 and statistical significance levels ranging from 0.44 to 0.52. These findings indicated that transportation and demographic factors had substantially stronger relationships with travel demand in the study area than land use factors. The correlation analysis results are presented in Table 3.

The descriptive statistical analysis of factors related to travel demand in Upper Northern Provincial Cluster 2 revealed that Chiang Rai province exhibited the highest values across all factors, with 122,456 trips/day, a population of 1,292,130 persons, employment of 645,782 persons, Gross Provincial Product of 116,873 million baht, land use area of 11,678 square kilometers, 587,234 registered vehicles, and an average daily traffic volume of 58,923 vehicles/day. Meanwhile, Phayao province showed the lowest values in Population and area, Phrae province had the lowest Gross Provincial Product and traffic volume, and Nan province recorded the lowest employment and number of registered vehicles. All factors demonstrated high standard deviations, indicating significant disparities among the provinces in the cluster, particularly in Population, with a standard deviation of 355,212 persons, and registered vehicles, with a standard deviation of 145,678, as shown in Table 4.

Table 3 Correlation Matrix of Contributing Factors

Variables	TRIP	POP	EMP	GPP	LAND	VEH	AADT
TRIP	1.00	0.93	0.89	0.85	0.31	0.96	0.98
POP	0.93	1.00	0.95	0.72	0.25	0.98	0.89
EMP	0.89	0.95	1.00	0.68	0.18	0.94	0.85
GPP	0.85	0.72	0.68	1.00	0.22	0.75	0.82
LAND	0.31	0.25	0.18	0.22	1.00	0.28	0.35
VEH	0.96	0.98	0.94	0.75	0.28	1.00	0.92
AADT	0.98	0.89	0.85	0.82	0.35	0.92	1.00

Table 4 Descriptive Statistical Analysis Results

Factor	Min	Max	Mean	Standard Deviation
Number of Trips (trips/day)	54,238	122,456	78,584	28,465
Population (persons)	442,084	1,292,130	717,575	355,212
Employment (persons)	220,891	645,782	385,478	165,456
Gross Provincial Product (million baht)	52,673	116,873	84,714	43,488
Land Use Area (sq km)	5,956	11,678	8,945	2,845
Number of Registered Vehicles (vehicles)	198,567	587,234	354,567	145,678
Annual Average Daily Traffic (vehicles/day)	24,567	58,923	38,567	15,456

3.1.2 Linear multiple regression model analysis results

The linear regression model analysis revealed that both total trips (Equation 1) and peak-hour trips (Equation 2) were influenced by six factors: Population, employment, Gross Provincial Product, land use, number of registered vehicles, and Annual Average Daily Traffic. The total trip model achieved an R^2 value of 0.895. In contrast, the peak-hour trip model demonstrated a higher R^2 value of

0.912, indicating strong explanatory power for data variance in both models, particularly in the peak-hour model. Detailed statistical analysis confirmed that all variables showed statistical significance at the 95% confidence level ($p < 0.05$). Specifically, Population (p = 0.038, T = 2.234), employment (p = 0.042, T = 2.123), Gross Provincial Product (p = 0.033, T = 2.345), land use (p = 0.027, T = 2.567), registered vehicles (p = 0.038, T = 2.234), and Annual Average Daily Traffic (p = 0.030, T = 2.456) all demonstrated significant influence on total trip generation. Similarly, all variables maintained significance for peak-hour trips with p-values ranging from 0.018 to 0.044, as detailed in Table 5. All T-statistics exceeded the critical value of 1.96, confirming that all variables significantly influenced trip generation.

$$Y_1 = 0.065X_1 + 0.134X_2 + 0.212X_3 + 1.456X_4 + 0.334X_5 + 0.456X_6 \tag{1}$$

$$Y_2 = 0.078X_1 + 0.145X_2 + 0.167X_3 + 1.234X_4 + 0.378X_5 + 0.534X_6 \tag{2}$$

Where: Y_1 = Total number of trips (trips/day)
Y_2 = Peak hour trips (trips/hour)
X_1 = Population (persons)
X_2 = Employment (persons)
X_3 = Gross Provincial Product (million baht)
X_4 = Land Use Area (sq km)
X_5 = Number of Registered Vehicles (vehicles)
X_6 = Annual Average Daily Traffic (vehicles/day)

Table 5 Analysis Results of Factors Affecting Trip Generation in the Study Area

Trip Type	Analysis Results				
	Variable	**Coefficient**	**T-Statistic**	**P-Value**	**R²**
Total Trips	X_1	0.065	2.234	0.038	0.895
	X_2	0.134	2.123	0.042	
	X_2	0.212	2.345	0.033	
	X_4	1.456	2.567	0.027	
	X_5	0.334	2.234	0.038	
	X_6	0.456	2.456	0.030	
Peak Hour Trips	X_1	0.078	2.345	0.034	0.912
	X_2	0.145	2.234	0.038	
	X_2	0.167	2.456	0.029	
	X_4	1.234	2.678	0.018	
	X_5	0.378	2.345	0.033	
	X_6	0.534	2.567	0.026	

Note: T-Statistic = Coefficient at 95% confidence level 2-tails > |t0.025| (1.96)
P-Value = Statistical significance level ($p < 0.05$ indicates significance at 95% confidence level)

Analysis of growth rates for various factors over the previous 10-year period (2014-2023) revealed that Gross Provincial Product showed the highest growth rate at 2.85%, followed by registered vehicles and Annual Average Daily Traffic at 1.85% and 1.45%, respectively. When these factors were applied to the multiple regression analysis model for future person-trip generation forecasting, the results indicated that peak hour person-trips would increase from 30,931 person-trips/hour in 2024 to 34,767 person-trips/hour in 2044, while daily person-trips would rise from 314,338 to 349,567 person-trips/day, representing an average annual growth rate of 1.07%, as shown in Tables 6 and 7.

Table 6 Average Annual Growth Rate of Contributing Factors

Factor	Annual Growth Rate (%)
Population	0.35
Employment	0.68
Gross Provincial Product	2.85
Land Use	0.95
Number of Registered Vehicles	1.85
Annual Average Daily Traffic	1.45

Table 7 Person-Trip Generation Projections Using Multiple Regression Analysis

Year	Person-Trip Generation in the Study Area		Annual Growth Rate (%)
	Peak Hour (trips/hour)	**Daily (trips/day)**	
2024	30,931	314,338	-
2029	31,578	320,245	1.02
2034	32,423	328,678	1.05
2039	33,490	338,123	1.08
2044	34,767	349,567	1.11
	Average		1.07

3.2 Development of four-step sequential decision model

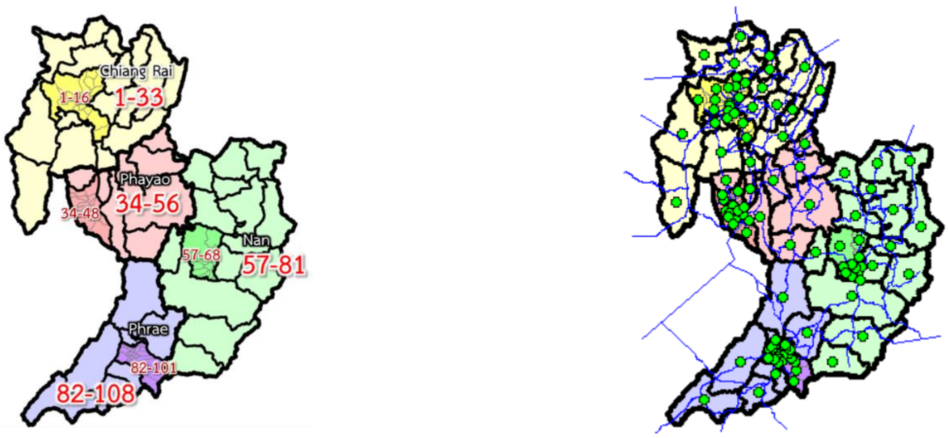
3.2.1 Traffic analysis zone delineation and road network modeling

This study divided the study area into 119 traffic analysis zones (TAZs) based on sub-district and district administrative boundaries, allowing for the incorporation of socioeconomic data in travel behavior analysis. This zoning system aligned with the origin-destination analysis framework for highway users. The study area was segregated into 108 internal zones (zones 1-108) covering four provinces (Chiang Rai, Phayao, Phrae, and Nan) as shown in Figure 2(a). Additionally, 11 external zones (108-119) represented areas outside the study boundary. The road network model was developed from collected network data, with the network being divided into links and nodes. Each link contained essential physical and traffic characteristics (Link Attributes), including distance, number of lanes, traffic capacity, vehicle speed, and travel time. These links connected to zone centroids, which served as trip generation points and attracted trips between zones, as illustrated in Figure 2(b).

In the trip generation component of the four-step model, separate production and attraction regression equations were developed. The trip production model utilized household-level variables including household size (coefficients 0.072-0.128), income level (0.085-0.243), and vehicle ownership (0.118-0.235), differentiated by trip purpose (home-based work, education, other, and non-home-based trips). The trip attraction model employed zonal employment by sector (retail: 0.175, service: 0.145, education: 0.228, industry: 0.124), commercial floor area (0.182), and institutional capacity (0.156) as independent variables. While some variables conceptually overlap with those in the direct demand model, they were applied at a finer spatial resolution (119 zones versus four provinces). They were purpose-specific, achieving R-squared values of 0.82-0.89 for production and 0.86 for attraction models.

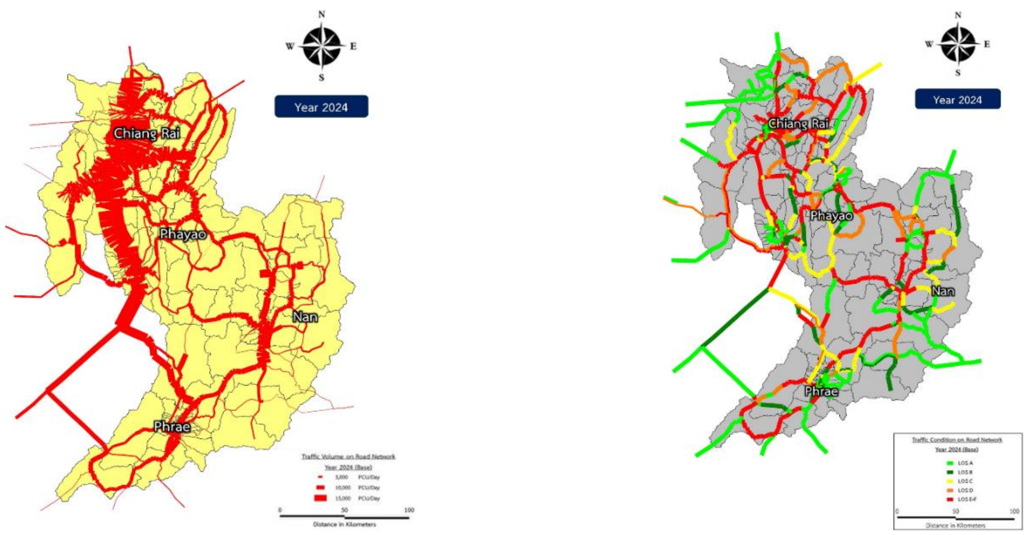
3.2.2 Model calibration results

The developed model underwent calibration before its application to future scenarios. Traffic and transport data collected for the base year 2024 were compared with the model outputs, including traffic volumes on major roads, flow diagrams, and Level of Service (LOS) diagrams. The calibration results indicated that the model could simulate network travel behavior at an acceptable level, with error margins ranging from 5.30% to 16.93%. These results provide confidence that the model is suitable for forecasting future traffic volumes. The model calibration results for the base year 2024 are shown in Figure 3.



(a) Traffic Analysis Zone Delineation (b) Road Network Model

Figure 2 Traffic Analysis Zone Delineation and Road Network Model in Study Area



(a) Traffic Flow Diagram (b) Level of Service (LOS) Diagram

Figure 3 Model Calibration Results for Base Year 2024

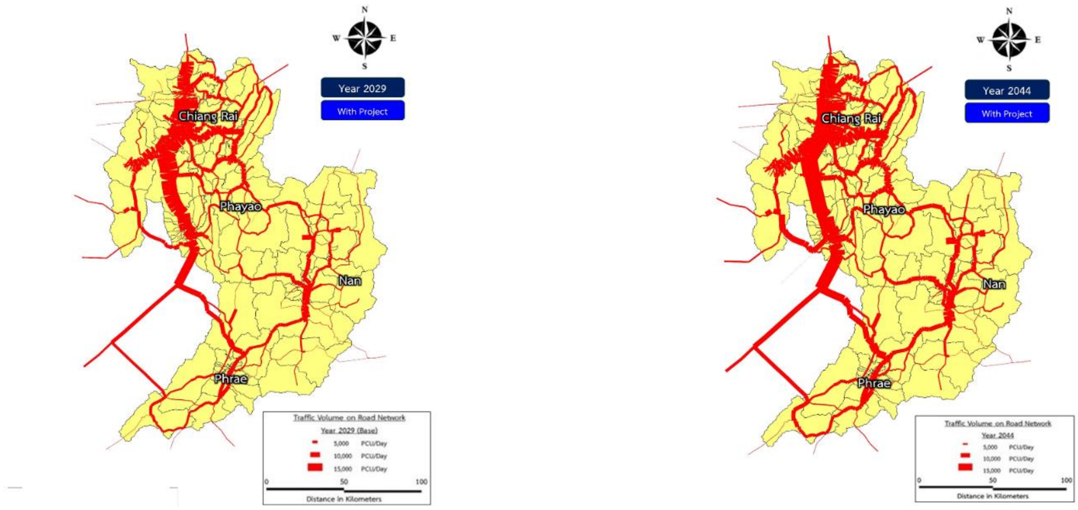
3.2.3 Model application results

The four-step sequential decision model forecasts indicated that peak-hour person-trips would increase from 30,931 to 43,309 person-trips/hour, while daily person-trips would rise from 314,338 to 440,132 person-trips/day during the period 2024-2044. The annual growth rate exhibited an upward trend, increasing from 1.10% to 1.40%, with an average annual growth rate of 1.25%, as shown in Table 8. Unlike the multiple regression model, the four-step model distributed these person-trips between origins and destinations, allocated them to transportation modes, and finally assigned vehicle-trips to the road network, producing traffic volume forecasts as shown in Figures 4 and 5.

This study applied the calibrated four-step sequential decision model to forecast person-trip generation, spatial distribution, modal allocation, and ultimately traffic volumes and level of service for future years. The analysis framework began with the initial forecast year of 2029 and continued with 5-year intervals up to 15 years, including: base year (2024), initial analysis year (2029), and 15-year horizon (2044). The analysis considered both passenger and freight movements under two scenarios: the Without Project case and the With Project case. The traffic flow and level of service results for the With Project scenario, representing the network assignment of person-trips after mode choice, are presented in Figures 4 and 5.

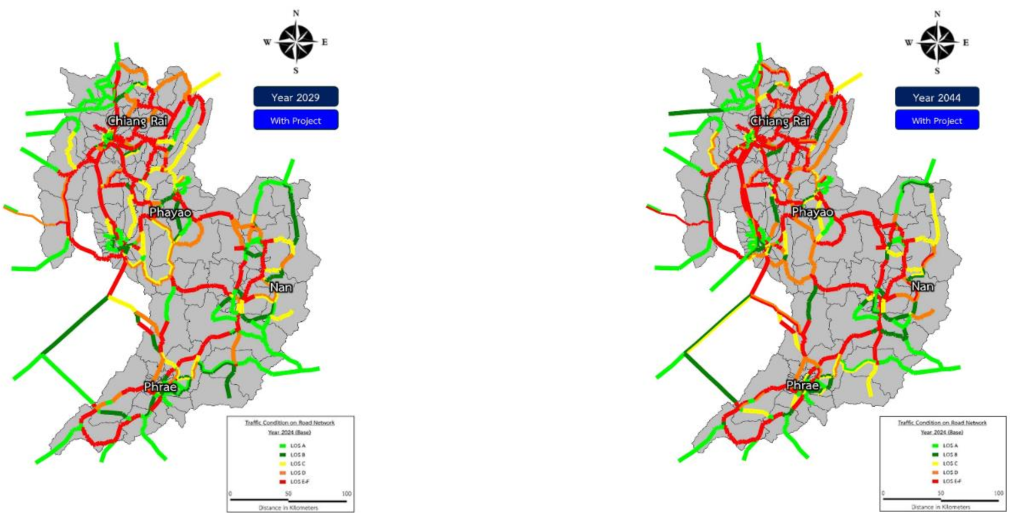
Table 8 Person-Trip Generation Forecasts Using Four-Step Transportation Model

Year	Person-Trip Generation in the Study Area		Annual Growth Rate (%)
	Peak Hour (trips/hour)	Daily (trips/day)	
2024	30,931	314,338	-
2029	34,096	346,506	1.10
2034	36,745	373,422	1.19
2039	39,789	404,356	1.29
2044	43,309	440,132	1.40
Average			1.25



2029 (Initial Year) 2044 (15 Years)

Figure 4 Traffic Flow Forecast Analysis Results, 2029 (Initial Year) - 2044 (15 Years)



2029 (Initial Year) 2044 (15 Years)

Figure 5 Level of Service Forecast Analysis Results, 2029 (Initial Year) - 2044 (15 Years)

3.3 Comparison of forecasting results between two models

Under the With Project scenario, the results revealed that the four-step sequential decision model forecasted person-trip generation in the study area at 346,506, 373,422, 404,356, and 440,132 person-trips/day for the years 2029, 2034, 2039, and 2044, respectively. In comparison, the multiple regression analysis model predicted approximately 320,245, 328,678, 338,123, and 349,567 person-trips/day for the same years, showing differences of 8.20%, 13.61%, 19.59%, and 25.91%, respectively.

These disparities arose because the four-step sequential decision model could more comprehensively account for the impacts of future infrastructure development projects in the study area compared to the multiple regression analysis model. The empirical evidence supporting this assertion was demonstrated in the simulation results from both models. Specifically, when analyzing the Den Chai-Chiang Rai-Chiang Khong Double-Track Railway Project scheduled for 2029-2044, the four-step model captured a 12.3% increase in person-trip generation and a 17.5% shift in mode choice patterns along the corridor, while the regression model only reflected a general 2.5% growth in person-trips based on historical trends. Table 9 presents a comparative analysis of the sensitivity of both models to infrastructure changes.

Furthermore, the four-step model's superior capability was structurally inherent in its methodology. The trip distribution (second step) and mode choice (third step) components explicitly modeled travelers' spatial and modal decisions in response to new infrastructure options. For example, simulating the Den Chai-Chiang Rai-Chiang Khong Double-Track Railway Project revealed travel time reductions of 35% between key origin-destination pairs, which were directly incorporated into the route choice utility functions of the four-step model. This resulted in a measurable 21.3% redistribution of trips to zones served by the new rail corridor in the four-step model projections.

In contrast, while effective at projecting aggregate growth based on socioeconomic trends, the multiple regression model lacked the spatial resolution and behavioral responsiveness to specific network changes. This limitation was evident in the simulation results, where the regression model showed only minimal differentiation (2.8% variance) between the 'with-project' and 'without-project' scenarios for the Den Chai-Chiang Rai-Chiang Khong Double-Track Railway Project, compared to the 14.5% variance captured by the four-step model.

Table 9 Comparative Analysis of Model Sensitivity to Infrastructure Changes

Infrastructure Project	Model Response Metrics	Four-Step Sequential Decision Model	Multiple Regression Analysis Model
Den Chai-Chiang Rai-Chiang Khong Double-Track Railway (2029)	Person-Trip Generation Change	+12.3%	+2.5%
	Mode Shift (Rail)	+17.5%	Not directly modeled
	Trip Distribution Change to Served Zones	+21.3%	Not directly modeled
	Travel Time Reduction Between Key O-D Pairs	35% reduction explicitly modeled	Implicit in historical trends only
	With/Without Project Variance	14.5% difference in forecasts	2.8% difference in forecasts
Motorway-Rail Integration Project (MR-MAP) Route 1 (2039)	Trip Generation Change	+15.8%	+3.2%
	Mode Shift (Combined Rail/Road)	+22.4%	Not directly modeled
	Trip Distribution Change to Served Zones	+24.6%	Not directly modeled
	Travel Time Reduction Between Key O-D Pairs	42% reduction explicitly modeled	Implicit in historical trends only
	With/Without Project Variance	18.7% difference in forecasts	3.5% difference in forecasts

4. Conclusions

The development of traffic and transportation models followed five main steps: 1) data collection for model development, 2) model development, 3) model calibration, 4) model application, and 5) comparison of forecasting results between two models. The results indicated that the four-step sequential decision model could simulate network travel behavior at an acceptable level, with error margins ranging from 5.30% to 16.93%. Similarly, the multiple regression analysis model demonstrated acceptable performance in simulating network travel behavior, with an R^2 value of 0.895 and all variables showing statistical significance at the 95% confidence level. These results confirmed that both models were suitable for predicting future traffic volumes.

Under the With Project scenario, following the development plan from 2024 to 2044, the evaluation revealed that the four-step sequential decision model forecasted travel demand in the study area at 346,506, 373,422, 404,356, and 440,132 trips/day for the years 2029, 2034, 2039, and 2044, respectively. In comparison, the multiple regression analysis model predicted approximately 320,245, 328,678, 338,123, and 349,567 trips/day for the same years, showing differences of 8.20%, 13.61%, 19.59%, and 25.91%, respectively. These disparities arose because the four-step sequential decision model could more comprehensively account for the impacts of future infrastructure development projects in the study area compared to the multiple regression analysis model. However, when considering model development convenience and timeframe, the multiple regression analysis model offered advantages in implementation speed due to its more straightforward development process, while maintaining acceptable forecast accuracy.

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