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Development and validation of free flow speed estimation models for multilane highways in Thailand

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Abstract

This study developed and evaluated free flow speed (FFS) estimation models for multilane highways in Thailand by applying multivariable linear regression. Data from 272 highway segments were analyzed considering the percentage of heavy vehicles, left shoulder width, and access point density. Highways were categorized into four-lanes and more-than-four-lanes configurations and further analyzed under different base free flow speeds (BFFS) ranging from 90 to 120 km/h. For four-lane highways, Model 1-2 (BFFS = 100 km/h) achieved the best predictive performance, with an R^2 of 0.9583, root mean squared error (RMSE) of 1.51, and mean absolute error (MAE) of 1.24. For more-than-four-lanes highways, Model 2-3 (BFFS = 110 km/h) performed best (R^2 = 0.9387, RMSE = 1.86, MAE = 1.46). All variables showed significant negative effects on FFS. The developed models provide practical tools for assessing roadway performance, thereby regulating speeds, and guiding infrastructure planning, enhancing safety and efficiency on Thai multilane highways.

Keywords: Free flow speed, Multilane highways, Multilinear regression, Traffic engineering

1. Introduction

Free flow speed (FFS) is a key traffic engineering parameter, representing the speed of vehicles under low-volume, uncongested conditions [1]. Accurate estimation of FFS is essential for highway design, traffic flow analysis, and infrastructure planning [2-5]. In Thailand, roadway characteristics and traffic compositions differ from international norms, which limits the direct applicability of standard models, such as those from the Highway Capacity Manual (HCM) [6]. Thai highways feature high variability in access points, inconsistent speed regulation, and mixed traffic comprising motorcycles and heavy vehicles, emphasizing the need for localized models.

International research highlights this necessity: in Malaysia, heterogeneous traffic comprising motorcycles and trucks necessitated customized modeling approaches [7]. In Indonesia, revisions to the HCM addressed outdated assumptions [8], and in India, localized models were essential to reflect operational conditions [9]. Similar findings from Brazil, Bosnia and Herzegovina, and the United States confirm that roadway geometry and traffic composition affect FFS, though exhibiting regional variations [2, 10-12]. However, in Thailand, existing FFS models are based on international standards and lack validation under local conditions. To address this gap, this study developed regression-based FFS models using access point density (APD), left shoulder width (LSW), and heavy vehicle percentage (HV%) and performed external validation across sites.

2. Materials and methods

2.1 Data collection

Data were collected from 272 multilane highway sites nationwide (Figure 1), selected under the following strict criteria: a minimum segment length of 3 km; flat and straight alignment (or wide-radius curves ≥800 m), no signalized intersections within 1 km, and consistent physical features such as median and frontage roads. Where median openings were present, they were spaced at least 1 km apart with adequate waiting lanes to prevent vehicles making U-turns from disrupting through traffic. The data were obtained from the Department of Highways National Traffic Monitoring System, which uses permanent traffic count stations equipped with automated sensors and GPS-based monitoring systems that continuously record vehicle speeds and volumes at 15-min intervals. Each site was observed over three consecutive days between 07:00 and 19:00 hours, excluding periods of adverse weather periods. Free flow conditions followed the HCM (2016) threshold of <500 vehicles per hour per lane. As only uncongested sites were included, this threshold was satisfied even during peak periods.

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Figure 1 Distribution of 272 multilane highway sites across Thailand.

2.2 Variable selection and justification

The selection of LSW, APD, and HV% as the primary predictors in the regression models was guided by both statistical significance and contextual relevance within Thai highway conditions. These variables exhibited high variability and strong correlations with FFS (Table 1). Previous studies have confirmed their influence: APD and HV% significantly influence FFS on multilane roads, while LSW has been shown to affect FFS under heterogeneous traffic conditions [7, 13-15]. Traffic volume was excluded because the study focused on free flow conditions, where congestion is minimal. Lane width was nearly uniform (~3.5m), and the motorcycle percentage represented a small fraction of traffic, mostly occupying the leftmost lanes or shoulders. Due to their limited variability and minor influence on FFS, both variables were excluded from the regression model.

Table 1 Descriptive statistics of predictor variables used in the regression models.

Variable		Mean	Std. Dev.	Minimum	Maximum
APD (access/km)	Four lanes	1.36	0.85	0.00	4.30
	More-than-four-lanes	1.94	1.46	0.00	7.30
LSW (m)	Four lanes	0.61	0.50	0.00	2.50
	More-than-four-lanes	0.88	0.85	0.00	2.50
HV% (%)	Four lanes	18.35	10.26	0.63	42.98
	More-than-four-lanes	29.02	13.34	3.94	55.28
LW (m)	Four lanes	3.52	0.23	3.00	5.25
	More-than-four-lanes	3.46	0.13	3.00	3.50
MC (%)	Four lanes	16.22	10.76	0.74	55.95
	More-than-four-lanes	8.74	8.61	0.99	37.72
FFS (km/h)	Four lanes	86.18	6.00	71.9	97.1
	More-than-four-lanes	79.33	8.50	63.20	99.00

2.3 Research framework

This study followed a systematic framework (Figure 2) based on data from 272 highway segments. The key predictors—LSW, APD, and HV%—were analyzed using multilinear regression. The data were split into 75% for training, 15% for testing, and 10% for external validation, using stratified random sampling to balance the distribution of four-lanes and more than four-lanes segments. The training set supported model calibration, the testing set enabled evaluation, and the validation set ensured generalizability. This approach aligns with best practices in traffic modeling, which typically allocate 70%–80% of the dataset for training [16].

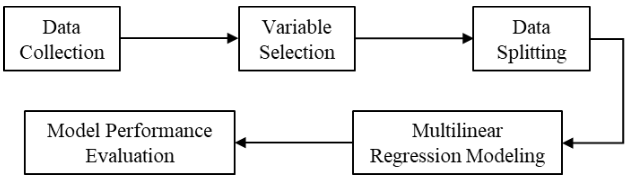
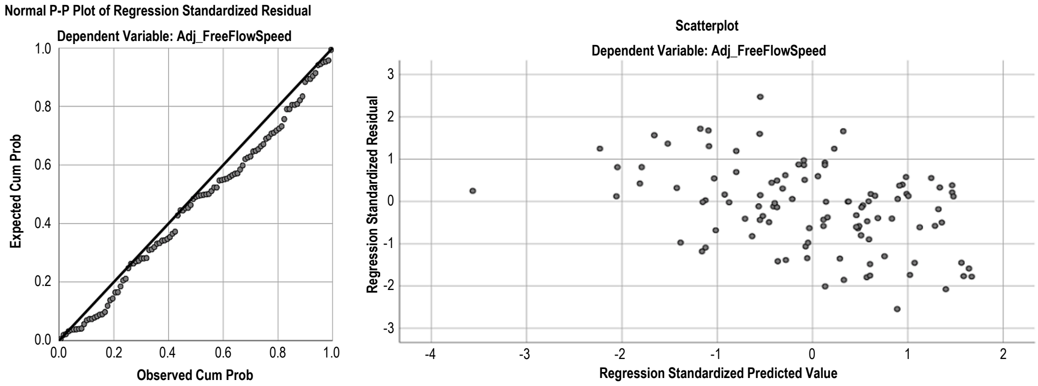


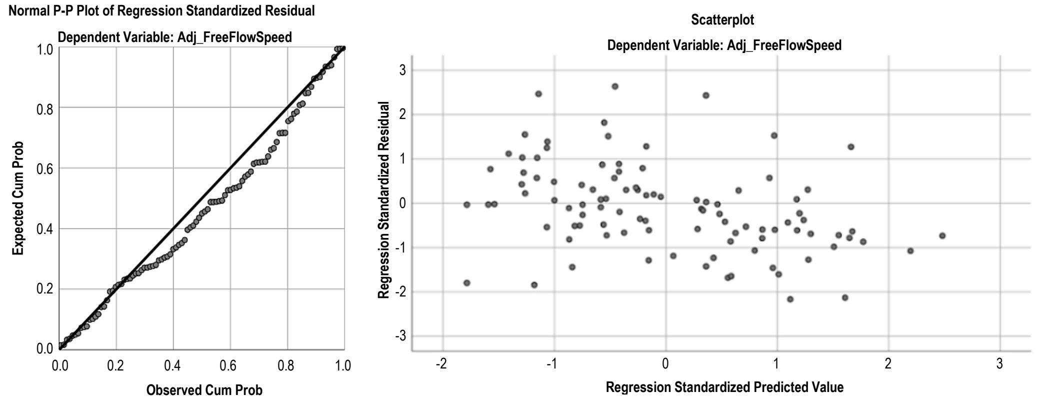
Figure 2 Framework for free flow speed model development.

2.4 Regression analysis

Prior to interpreting the regression results, the key statistical assumptions of normality, linearity, and homoscedasticity were examined to ensure the validity of the developed models, as illustrated in Figure 3.



(a)



(b)

Figure 3 Residual analysis of (a) four-lane highways and (b) more-than-four-lane highways.

For both four-lane and more-than-four-lane highways, the P–P plot indicated that the residuals closely followed the diagonal line, indicating an approximate normality, while the scatterplot confirmed linearity and homoscedasticity without significant outliers, thereby confirming that regression assumptions were reasonably satisfied.

2.5 Model validation and performance

Model performance was assessed using coefficient of determination (R^2), root mean squared error (RMSE) and mean absolute error (MAE), with fivefold cross-validation applied to the training data to ensure robustness. RMSE and MAE measure prediction errors; lower values therefore indicate a better fit. R^2 indicates how well the model explains the variance in the data, with values closer to 1 indicating stronger performance. The results in Table 2 demonstrated high accuracy and generalizability, with R^2 values of 0.991 for four-lane highways and 0.996 for more-than-four-lane highways. Additionally, the low RMSE and MAE values further indicated strong predictive capability.

Table 2 Performance of the multilinear regression model using fivefold cross-validation on the training set.

Fold		RMSE	MAE	R^2
1	Four-lane	2.18	1.62	0.980
	More-than-four-lanes	3.77	2.81	0.987
2	Four-lane	1.62	1.32	0.991
	More-than-four-lanes	1.99	1.54	0.996
3	Four-lane	2.48	1.86	0.976
	More-than-four-lanes	3.18	2.27	0.993
4	Four-lane	2.68	2.04	0.969
	More-than-four-lanes	3.58	2.45	0.991
5	Four-lane	2.35	1.73	0.967
	More-than-four-lanes	3.55	2.36	0.989

The general equation, as adopted from the HCM method (HCM, 2022) to estimate the FFS of multilane highways, is presented in Equation 1.

$$FFS = BFFS - \sum_k f_k \quad \text{Equation (1)}$$

FFS = free flow speed of the multilane highway segment; $BFFS$ = base free flow speed for the multilane highway segment; f_k = adjustment factors for different k roadway and roadside characteristics influencing FFS, for example, adjustment for lane width (f_{LW}), adjustment for total lateral clearance (f_{TLC}), adjustment for median type (f_M), and adjustment for APD (f_A).

3. Results

3.1 Model accuracy and predictive performance for four-lane highways

The regression analysis on four-lane highways, as presented in Table 3, indicates that Model 1-2 (BFFS = 100 km/h) performs the best overall in terms of prediction accuracy, with the lowest prediction error (2.500) and a high R^2 of 0.973. Model 1-3 (BFFS = 110 km/h) demonstrates comparable performance, with not only a slightly higher R^2 of 0.974 but also a higher prediction error of 3.999. In contrast, Model 1-1 (BFFS = 90 km/h) is the least effective, exhibiting a lower R^2 of 0.607 and the highest prediction error (4.482). In terms of statistical significance, all three models demonstrate highly significant ($p < 0.05$).

Table 3 Summary and coefficients of regression models on four-lane highways.

Model 1	R^2	Std. Error of the Estimate	F	Sig. (ANOVA)
Model 1-1 (BFFS = 90 km/h)	0.607	4.482	52.529	0.000
Model 1-2 (BFFS = 100 km/h)	0.973	2.500	1238.707	0.000
Model 1-3 (BFFS = 110 km/h)	0.974	3.999	1290.158	0.000

The coefficient analysis (Table 4) demonstrates that LSW, APD, and HV% significantly reduce FFS. APD shows the strongest influence on four-lane highways, with each additional roadside access point reducing FFS by 4.2–6.8 km/h, thereby highlighting the disruptive effect of roadside friction. HV% decreases FFS by 0.27–0.46 km/h per 1% increase, with a cumulative impact resulting from high truck volumes. Reductions in LSW decrease FFS by 5.7–8.7 km/h per meter, reflecting the importance of adequate lateral clearance for driver comfort and maneuverability. These findings highlight the need for roadside access management, freight vehicle regulation, and adequate shoulder provision to improve operating speeds and enhance overall multilane highway performance.

Table 4 The coefficients of FFS regression models on four-lane highways.

Coefficients							
Model 1	Variables	Unstandardized coefficients		Standardized coefficients	t	Sig.	95.0% confidence interval for B (Lower, Upper)
		B	Std. Error	Beta			
Model 1-1 (BFFS = 90 km/h)	LSW	−2.703	0.750	−0.302	−3.601	0.000	(−4.191, −1.214)
	APD	−1.682	0.445	−0.370	−3.780	0.000	(−2.564, −0.799)
	HV%	−0.070	0.035	−0.210	−2.006	0.048	(−0.139, −0.001)
Model 1-2 (BFFS = 100 km/h)	LSW	−5.724	0.419	−0.299	−13.671	0.000	(−6.554, −4.893)
	APD	−4.231	0.248	−0.435	−17.047	0.000	(−6.554, −4.893)
	HV%	−0.267	0.019	−0.377	−13.782	0.000	(−0.305, −0.229)
Model 1-3 (BFFS = 110 km/h)	LSW	−8.744	0.670	−0.280	−13.060	0.000	(−10.073, −7.416)
	APD	−6.780	0.397	−0.428	−17.081	0.000	(−7.568, −5.993)
	HV%	−0.464	0.031	−0.402	−14.986	0.000	(−0.526, −0.403)

Presented below are three regression equation variations for four-lane highways derived from Equation 1. Each model follows a linear regression framework, in which FFS is expressed as a function of three independent variables:

Model 1-1, $FFS = 90 - 2.703*(2.5 - LSW) - 1.682*APD - 0.070*HV\%$ Equation (2)

Model 1-2, $FFS = 100 - 5.724*(2.5 - LSW) - 4.231*APD - 0.267*HV\%$ Equation (3)

Model 1-3, $FFS = 110 - 8.744*(2.5 - LSW) - 6.780*APD - 0.464*HV\%$ Equation (4)

These equations (Equations 2–4) represent FFS models for different BFFS, incorporating the effects of LSW, APD, and HV%. The negative coefficients indicate that as APD and HV% increase, FFS decreases. Similarly, a lower LSW (below 2.5 m) leads to a reduced FFS. Figure 4 shows that Model 1-2 (BFFS = 100 km/h) provides the best fit between predicted and observed FFS, followed by Model 1-3 (BFFS = 110 km/h), while Model 1-1 (BFFS = 90 km/h) exhibits the weakest performance, with greater data variability.

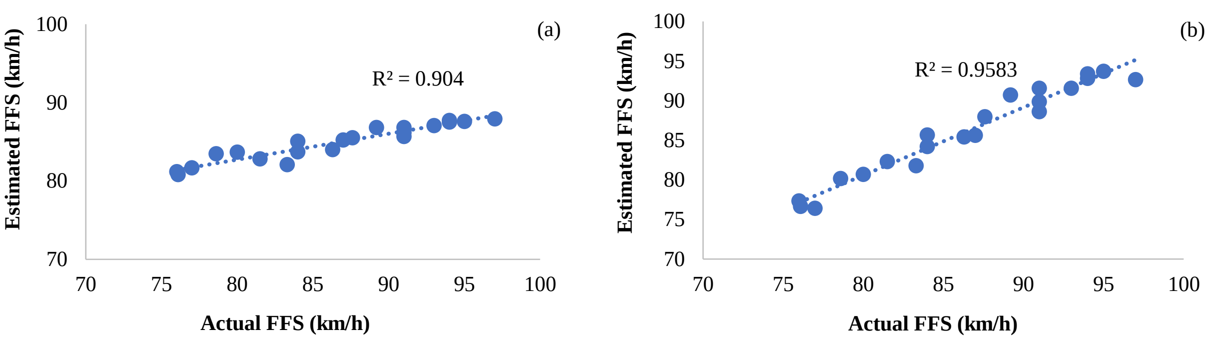


Figure 4 Comparison of estimated and actual free flow speeds for four-lane highways: (a) Model 1-1 (BFFS = 90 km/h); (b) Model 1-2 (BFFS = 100 km/h); (c) Model 1-3 (BFFS = 110 km/h).

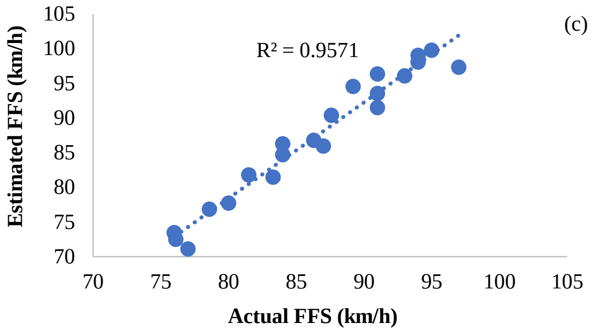


Figure 4 (continued) Comparison of estimated and actual free flow speeds for four-lane highways: (a) Model 1-1 (BFFS = 90 km/h); (b) Model 1-2 (BFFS = 100 km/h); (c) Model 1-3 (BFFS = 110 km/h).

As shown in Table 5, Model 1-2 (BFFS = 100 km/h) performs best, exhibiting the highest R^2 (0.9583) and the lowest RMSE (1.51) and MAE (1.24), accurately reflecting prevailing highway conditions in Thailand. Model 1-3 demonstrates comparable performance, whereas Model 1-1 exhibits the lowest predictive accuracy. The findings highlight that roadway geometric and traffic composition factors, particularly LSW, APD, and HV%, exert significant influence on FFS.

Table 5 Model evaluation performance for different free flow speeds on four-lane highways.

Model	RMSE	MAE	R^2	Overall ranking
Model 1-1 (BFFS = 90 km/h)	4.65	4.05	0.9040	3rd
Model 1-2 (BFFS = 100 km/h)	1.51	1.24	0.9583	1st
Model 1-3 (BFFS = 110 km/h)	3.48	2.70	0.9571	2nd

3.2 Model accuracy and predictive performance for more-than-four-lane highways

For more-than-four-lane highways, four regression models were evaluated using BFFS of 90 to 120 km/h, respectively, as summarized in Table 6. Model 2-3 (BFFS = 110 km/h) demonstrated the highest predictive accuracy (R^2 = 0.989, SE = 3.460). Although Model 2-4 showed a similarly high R^2, its higher error rendered Model 2-3 the more reliable model. All models were statistically significant ($p < 0.001$), confirming their robustness and reliability for prediction.

Table 6 Summary and coefficients of regression models on more-than-four-lane highways.

Model 2	R^2	Std. error of the estimate	F	Sig. (ANOVA)
Model 2-1 (BFFS = 90 km/h)	0.843	5.673	171.787	0.000
Model 2-2 (BFFS = 100 km/h)	0.973	3.838	1139.524	0.000
Model 2-3 (BFFS = 110 km/h)	0.989	3.460	2855.026	0.000
Model 2-4 (BFFS = 120 km/h)	0.987	4.889	2413.781	0.000

Regression coefficients (Table 7) indicate that LSW, APD, and HV% negatively affect FFS on more-than-four-lane highways. HV% emerges as the most influential variable, with each 1% increase reducing FFS by 0.29–0.82 km/h. Given Thailand's substantial truck traffic volumes, this cumulative effect significantly reduces operating speeds, underscoring the critical role of effective freight management policies. APD reduces FFS by 0.9–4.4 km/h, while reductions in LSW further decrease FFS by 2.5–8.7 km/h. These results emphasize the need for targeted freight regulation, strategic access control, and provision of adequate shoulder width to enhance operational efficiency and safety.

Table 7 The coefficients of FFS regression models on more-than-four-lane highways.

Coefficients							
Model 2	Variables	Unstandardized coefficients		Standardized coefficients	t	Sig.	95.0% confidence interval for B
		B	Std. Error	Beta			(Lower, Upper)
Model 2-1 (BFFS = 90 km/h)	LSW	-2.469	0.524	−0.222	-4.713	0.000	(-3.509, -1.429)
	APD	−0.917	0.339	−0.156	−2.705	0.008	(−1.590, −0.244)
	HV%	−0.288	0.025	−0.670	−11.408	0.000	(−0.339, −0.238)
Model 2-2 (BFFS = 100 km/h)	LSW	−4.532	0.354	−0.251	−12.785	0.000	(−5.235, −3.828)
	APD	−2.090	0.229	−0.218	−9.108	0.000	(−2.545, −1.634)
	HV	−0.466	0.017	−0.668	−27.269	0.000	(−0.500, −0.432)
Model 2-3 (BFFS = 110 km/h)	LSW	−6.594	0.320	−0.258	−20.638	0.000	(−7.228, −5.960)
	APD	−3.262	0.207	−0.241	−15.774	0.000	(−3.673, −2.852)
	HV%	−0.644	0.0.015	−0.652	−41.797	0.000	(−0.675, −0.614)
Model 2-4 (BFFS = 120 km/h)	LSW	−8.657	0.451	−0.260	−19.173	0.000	(−9.553, −7.760)
	APD	−4.435	0.292	−0.252	−15.176	0.000	(−5.105, −3.854)
	HV%	−0.822	0.022	−0.640	−37.749	0.000	(−0.865, −0.779)

For both four-lanes and more-than-four-lanes models, narrow confidence intervals indicate statistically precise and reliable parameter estimates. The effects of APD, LSW, and HV% consistently exhibit negative relationships with FFS, confirming their robustness as key predictors across all model configurations. Presented below are four regression equation variations for more-than-four-lane highways based on Equation 1.

Model 2-1, FFS = 90 − 2.469*(2.5 − LSW) − 0.917*APD − 0.288*HV% Equation (5)

Model 2-2, FFS =100 − 4.532*(2.5 − LSW) − 2.090*APD − 0.466*HV% Equation (6)

Model 2-3, FFS =110 − 6.594*(2.5 − LSW) − 3.262*APD − 0.644*HV% Equation (7)

Model 2-4, FFS =120 − 8.657*(2.5 − LSW) − 4.435*APD − 0.822*HV% Equation (8)

Model-specific equations (Equations 5–8) illustrate the functional influence and relative contribution of each variable. The negative coefficients indicate that increases in APD and HV% correspond to a reduction in FFS. Likewise, when LSW is <2.5 m, FFS decreases accordingly. Figure 5 presents the comparative results for more-than-four-lane highways. Model 2-3 (BFFS = 110 km/h) demonstrates the highest predictive accuracy, with Models 2-2 and 2-4 showing comparable yet slightly less stable performance. Model 2-1 once again exhibits the weakest correlation and lowest predictive reliability.

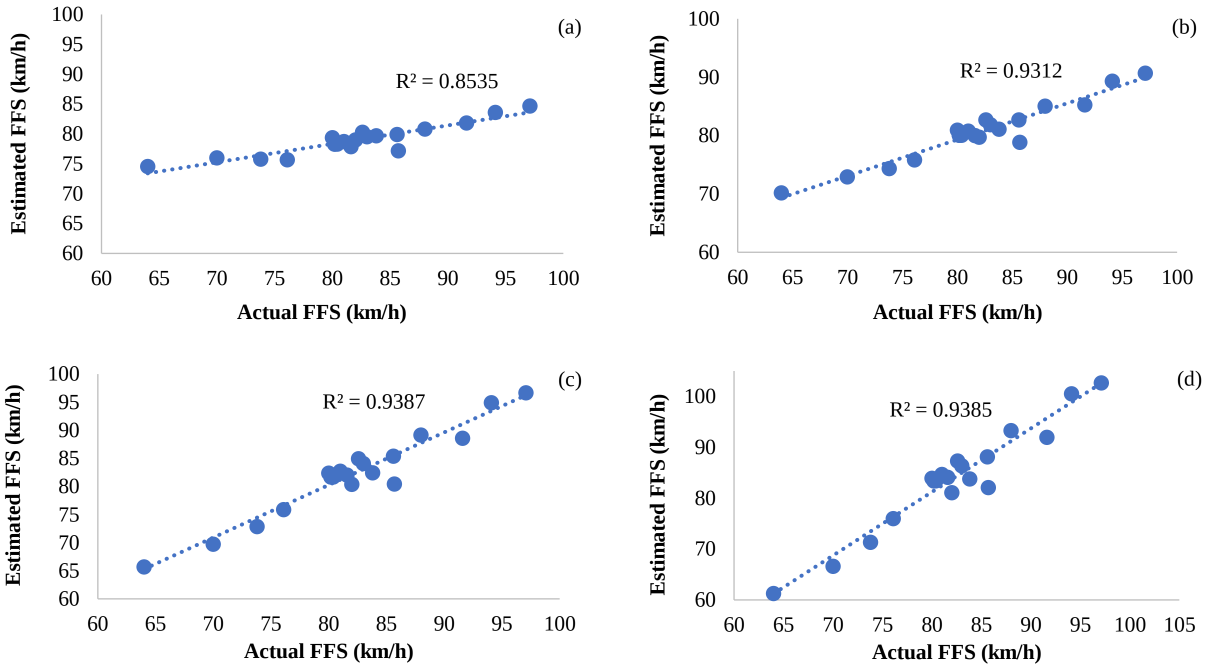


Figure 5 Comparison of estimated and actual free flow speeds for more-than-four-lane highways: (a) Model 2-1 (BFFS = 90 km/h); (b) Model 2-2 (BFFS = 100 km/h); (c) Model 2-3 (BFFS = 110 km/h); (d) Model 2-4 (BFFS = 120 km/h).

Among the four models tested, Model 2-3 (BFFS = 110 km/h) exhibited the best performance, with the highest R^2 (0.9387) and the lowest values of RMSE (1.86) and MAE (1.46), as presented in Table 8, indicating the model's superior accuracy and reliability.

Table 8 Model performance for different FFS models on more-than-four-lane highways.

Model 2	RMSE	MAE	R-squared	Overall Ranking
Model 2-1 (BFFS = 90 km/h)	6.09	4.92	0.8535	4th
Model 2-2 (BFFS = 100 km/h)	3.43	2.51	0.9312	2nd
Model 2-3 (BFFS = 110 km/h)	1.86	1.46	0.9387	1st
Model 2-4 (BFFS = 120 km/h)	3.45	3.05	0.9385	3rd

Model 2-3, represented by FFS = 110 − 6.594*(2.5 − LSW) − 3.262*APD − 0.644*HV% (Equation 7), estimates the FFS for more-than-four-lane highways using a BFFS of 110 km/h, adjusted by LSW, APD, and HV%. Decreases in LSW or increases in APD and HV% result in lower estimated FFS values.

3.3 External validation and generalizability

The external validation dataset comprised 27 independent more-than-four-lane highway sites (14 four-lanes and 13 more-than-four-lanes segments) across the central, northern, and northeastern regions of Thailand. The segments encompassed diverse roadway features such as variations in shoulder widths, geometric alignments, and access configurations. Traffic composition varied in terms of the proportions of heavy vehicle and motorcycles, while APDs reflected both low- and high-access roadside friction conditions.

Four-lanes and more-than-four-lanes models achieved R^2 of 0.926 and 0.988, respectively, with low RMSE and MAE, thereby demonstrating strong predictive performance and robust external validity (Table 9).

Table 9 Model performance comparison for free flow speed on external data.

Model		RMSE	MAE	R^2
Four-lane highways	Selected test	1.51	1.24	0.9583
	External test	1.44	1.13	0.9257
Multilane highways	Selected test	1.86	1.46	0.9387
	External test	1.78	1.45	0.9875

4. Discussions

This study identifies LSW, APD, and HV% as strong predictors of FFS on multilane highways in Thailand. All three variables negatively affect FFS, confirming that narrower shoulders (<2.5 m), a higher frequency of roadside access points, and greater proportions of heavy vehicles lead to reduced operating speeds.

For four-lane highways, Model 1-1 (BFFS = 90 km/h) yielded the lowest explanatory power (R^2 = 0.607) due to limited data variability and few segments operating near 90 km/h. In comparison, Model 1-2 (100 km/h) demonstrated stronger performance and better alignment with actual traffic conditions, confirming its suitability as a representative model for Thai multilane highways. Similarly, Model 2-3 with a BFFS of 110 km/h achieved the best performance for more-than-four-lane highways, reflecting the prevailing FFS under Thai traffic conditions.

Compared with the HCM (2022), the influence of heavy vehicles and access points appears to be stronger in Thailand, reflecting greater traffic heterogeneity and less consistent lane discipline. Similar findings have been reported in Malaysia and India [7, 9], where the direct application of HCM-based models tended to overestimate or underestimate observed speeds.

External validation further substantiated the models' robustness, with minimal performance loss on unseen sites. These accurately capture realistic driving conditions and representative BFFS values for Thailand. However, broader contextualization through comparative analysis with models from other geographic regions could provide additional insights. For instance, studies [2] and [10] revealed that variations in posted speed limits and geometric design features significantly affect model sensitivity, highlighting the necessity of context-specific calibration. Beyond Thailand, the developed models may also be applicable to other Southeast Asian countries such as Malaysia, Indonesia, Vietnam, and the Philippines. With appropriate local calibration, this framework offers a regionally adaptable tool for modeling heterogeneous traffic conditions and diverse roadway environments.

5. Conclusions

This study developed and validated multilinear regression models for estimating FFS on multilane highways in Thailand, focusing on APD, LSW, and HV%. Data were divided into training (75%), testing (15%), and external validation (10%) sets, with fivefold cross-validation. Separate models were created for four-lane and more-than-four-lane highways, with performance evaluated across varying BFFS.

The models demonstrated high predictive accuracy, particularly Model 1-2 (BFFS = 100 km/h) for four-lane highways and Model 2-3 (BFFS = 110 km/h) for multilane highways. Performance metrics (R^2, RMSE, and MAE) and external validation confirmed the models' strong goodness-of-fit, generalizability, and practical applicability across varying roadway conditions in Thailand. All three variables significantly reduce FFS, highlighting the influence of local traffic composition and roadway characteristics.

The models provide practical tools for regional transportation planning, roadway design, and speed management, supporting level of service analysis, capacity estimation, and the selection of appropriate design speeds. They inform decisions on setting posted speed limits, particularly for segments with narrow shoulders, high heavy vehicle proportions, or dense access points. In such cases, localized interventions, such as speed-limit adjustments, access management, or targeted enforcement, can be implemented to enhance safety and operational efficiency [3, 7, 15, 17]. Practical implementation challenges, such as variability in driver behavior and limited data availability, can be mitigated through continuous traffic monitoring, integration into traffic management systems, and periodic model recalibration.

Key limitations include the relatively small dataset, reliance on spot-speed measurements, and the exclusion of variables such as slope, median design, and roadside features, which may affect driver comfort and operating speeds. Additionally, external factors, including weather conditions, enforcement levels, and seasonal variations, were not considered due to data constraints. Future studies should expand the dataset and include additional variables to enhance model applicability and generalizability. Overall, the developed FFS models provide context-specific and evidence-based tools for Thai multilane highways, bridging the gap between international methodologies and local traffic characteristics, and offering a reliable foundation for both planning and operational decision making.

6. Acknowledgements

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