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Evaluation of the Highway Capacity Manual (HCM) and Thailand's Department of Highways' approaches to estimating the capacity of a multilane highway segment via the empirical method

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Abstract

This study aims to evaluate the methods used by the Thailand Department of Highways (DOH) and the Highway Capacity Manual (HCM 2010 and HCM 2016) for estimating the capacity of an urban multilane highway segment in Thailand, by comparing these estimates with the empirical capacity derived from a speed-flow plot. Field data were collected from a six-lane urban highway segment in Thailand, followed by documentation of the roadway conditions and analysis of vehicle composition. Capacity estimates were calculated using the DOH and HCM methods prior to comparing them to the empirically measured capacity. The results showed that the empirical capacity was 1,619 pc/h/ln. The capacities estimated using the HCM 2010 and HCM 2016 methods were 34.8% and 35.3% greater than the empirically measured capacity, respectively, while the capacity estimated using the DOH method was 14.1% lower than the measured capacity. These findings indicate significant discrepancies in the estimates produced by the three models, when applied to the multilane highways segment. Given that the DOH model has not been updated in over two decades, this study concludes that its accuracy in capacity estimation may be compromised by evolving factors, such as driver behavior, traffic flow characteristics, vehicle types, and vehicle performance. Moreover, the DOH method's omission of variables (including access point density, median type, and terrain type) may further affect its accuracy. Similarly, since HCM 2010 and HCM 2016 are tailored to the United States, using both models to estimate the capacity of the multilane highway segment of interest may lead to errors due to differences in driver behaviors between Thai and American drivers, distinct traffic flow characteristics, the model's omission of the percentage of motorcycles, and the overestimation of speed at capacity on the highway segment.

Keywords: Highway capacity, Traffic, Multilane highway, Speed-Flow diagram, Highway capacity manual, Field data

1. Introduction

Estimating highway capacity is crucial when managing road traffic because accurate capacity estimates lead to appropriate traffic planning, to cope with demand and the volume of vehicles traversing the roadways. Either overestimating or underestimating road capacity may lead to diminished efficiency in urban planning, road design, and traffic operations, especially during peak periods [1, 2]. Overestimating the capacity of a roadway can directly lead to traffic congestion, as the actual capability of the roadway to allow the flow of vehicles during peak hours falls short of the designed capacity. On the contrary, underestimating a roadway capacity can lead to inefficient traffic operations, since traffic planners and controllers may divert vehicles to a different route, despite the roadway still having room to carry more vehicles.

There are various methods for estimating highway capacity, with the commonly favored international approach being the method proposed by the Highway Capacity Manual (HCM) [3, 4]. The HCM's highway capacity estimation models for freeways, multilane highways, and rural highways are extensively used worldwide, while the Thailand Department of Highways (DOH) developed its own model and applied it for the first time in 2003, to estimate the capacities of the Thai roadways under its authority. It is captivating to investigate whether the HCM model, which has been regarded as one of the most trustworthy capacity estimation tools, by transportation professionals globally, is also effective in estimating a highway's capacity in Thailand. On the other hand, the DOH's model has been in use for a while and was created specifically for Thai roads. Examining whether the model needs to be updated is intriguing because variables pertaining to driver behavior, traffic flow characteristics, vehicle types, and vehicle performance have changed over time.

The objective of this research is to compare the capacities estimated using HCM 2010, HCM 2016, and the DOH's models with the empirical capacity. This involves collecting traffic data to plot speed-flow diagrams for determining empirical capacity. Subsequently, data on existing physical roadway conditions, such as lane width, shoulder width, access point density, posted speed limit, median type, roadside condition, and the proportion of relevant vehicles, are gathered as input variables for both models under consideration. This comparative analysis aims to identify differences between the capacities derived from these three models and the empirically measured capacity. This research focuses on a multilane highway segment in Thailand, which experiences significant traffic congestion during the rush hour.

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2. Literature review

The multilane highway capacity estimation models of HCM possess several aspects that make them different from the model developed by the Thailand Department of Highways. Despite the fact that all of these models take into account some comparable parameters, such as lane width and lateral clearance, the methodologies used to calculate capacities and the values of parameters used in these models are different. To be more specific, the DOH model takes into account the percentage of motorcycles, the percentage of heavy vehicles (trucks and buses), and the categorization of roadside conditions into urban and rural settings [5], whereas HCM 2010 and HCM 2016 overlook these factors. In contrast to the DOH model, the median type, free-flow speed, and access point density are taken into account in the HCM 2010 and HCM 2016 capacity estimation models [3, 4], as summarized in Table 1. Furthermore, the calculation methodologies of these models are elaborated in Section 3.

Table 1 Comparison of parameters included in the multilane road capacity estimation models

Parameter	HCM 2010 Model	HCM 2016 Model	DOH Model
Lane Width	✓	✓	✓
Shoulder Width	✓	✓	✓
Median Type	✓	✓	—
Access Point Density	✓	✓	—
Free-Flow Speed	✓	✓	—
Percentage of Heavy Vehicles	—	—	✓
Percentage of Motorcycles	—	—	✓
Urban/Rural Setting	—	—	✓

The HCM models, developed and designed by traffic engineers and experts in the United States, can generally estimate highway capacity, albeit with potential discrepancies from actual capacity due to various factors, such as the fluctuations of vehicle compositions in traffic streams at different times and the dynamics of driver behaviors within specific locales. The dynamic and intricate nature of road traffic is attributed to factors such as driver aggression and regional variations, as noted by Hamad and Abuhamda [6], and Akçelik [7]. Previous studies also suggested that capacity is not static throughout time because it might fluctuate at any given moment for a number of reasons, such as weather, the emotions of drivers, and unintended occurrences [2, 8-11].

Typically, the empirical capacity of each highway segment in specific conditions can be determined by collecting traffic flow data over short intervals, usually every 5 minutes, along with estimating the average vehicle speeds during those intervals. Subsequently, a speed-flow diagram is plotted. The vehicular flow rate at each point immediately prior to when the average speed of vehicles abruptly drops or suddenly before the traffic density sharply increases (pre-breakdown), indicating the transition from uncongested to congested flow, is determined [1]. The average flow rate at this moment represents the capacity [2, 12-15]. A good highway capacity estimation model should yield values which are closely aligned with the observed capacity obtained from the empirical method.

Previous studies have compared and assessed the outcomes of highway capacity estimation techniques across multiple schemes in various countries. Notably, these studies fall into two main categories: direct empirical methods and indirect empirical methods [16]. A number of studies conducted both direct and indirect empirical methods, by evaluating the selected highway capacity estimation models with the empirical highway capacity, using the relationship between speeds and flow rates from field data [1, 2, 7, 9, 17-19]. Asgharzadeh and Kondyli [1] compared the capabilities of four methods for estimating the capacity of a freeway segment in the United States: the HCM method, the Van Aerde method, the PLM model, and the SFI model. The study found that the Van Aerde method provided the capacity closest to the empirical value obtained from a speed-flow diagram, while the PLM method yielded the highest capacity and the HCM method resulted in the lowest capacity [1]. Jayaratne and Pasindu [17] evaluated the effectiveness of the HCM 2010 method for estimating the capacity of a multilane urban highway in Sri Lanka. The results showed that the HCM 2010 approach is inappropriate for assessing the capacity of multilane highways in Sri Lanka since typical vehicle speeds are lower than those expected by the method [17].

A recent study was conducted by Adnan et al. [19], to evaluate the effectiveness of the HCM 2010 and the Malaysian Highway Capacity Manual (MHCM) 2011 models on predicting the density and capacity of a four-lane multilane highway in Malaysia. The study compared the densities estimated using these models with the density obtained from the empirical method via statistical analyses. The authors suggested that the MHCM's model provided more accurate results when measuring the density of the highway compared to the HCM's model [19]. Roh [20] evaluated the performance of the Korea Highway Capacity Manual's (KHCM) model on estimating the capacity of urban freeway segments in Seoul, South Korea, by analyzing the effects of heavy vehicles in the traffic streams. This study found that the capacities produced by the KHCM's deterministic model were significantly different from the capacities measured via the empirical method. Ultimately, the author recommended that the KHCM's model should be revised to capture the changes in the performance of modern heavy vehicles [20].

A study was conducted by Jain et al. [21], to perform capacity estimation via an empirical method on two-lane undivided highways in a mountainous area in India and compare the results with the capacities estimated using the Chinese HCM and Indonesian HCM models, by focusing on the effects of gradients. The results showed that the capacity of highways decreased as the magnitude of the gradient increased. The study also concluded that highway capacity and vehicular speed are affected by gradient, weather, and pavement conditions. Eventually, the capacities estimated via the empirical method were similar to the capacities estimated using the Chinese HCM and Indonesian HCM models [21]. For a case study in Thailand, Ringkananont and Siridhara [22] conducted measurements of the capacity of highways, specifically four-lane and two-lane roads, to determine the empirical capacity. The results indicated that the Northwestern model, Underwood and Edie-Low model, and Greenberg and Edie-Jam model provided capacities that were lower than the empirical capacities of the highways obtained from the speed-flow relationship [22].

On the other hand, some studies were found to merely follow indirect empirical methods by employing traffic simulation models to estimate the actual highway capacity and compare it to the capacities estimated via the selected highway capacity estimation models [23-27]. Chaipanha et al. [25] conducted an experimental estimation of the capacity of four-lane rural highways in Thailand, featuring raised median types. A microscopic traffic simulation model was applied to indirectly obtain the capacity and the results were then compared with the capacity calculated using the HCM 2010 method. The study found that the capacity of the representative highways, under survey conditions, was 1,524 passenger cars per hour per lane (pc/h/ln), which is 23.5% lower than the capacity calculated using the HCM 2010 method [25]. Additionally, Chaipanha and Kaewwichian [27] conducted an experimental estimation of the capacity of two-lane rural highways in Thailand. The study found that the capacity of the two-lane rural highways, obtained indirectly from the traffic simulation model with VISSIM software, was 14% greater than the capacity calculated using the HCM 2010 method [27].

To put it succinctly, a number of studies attempted to compare the estimated capabilities derived from different models with the anticipated real capacities noted by direct and indirect empirical approaches. However, none of these studies attempted to address differences in multilane highway capacity estimation between the DOH and HCM models, when compared to the speed-flow plot. Therefore, it is interesting to investigate which model can provide a more accurate estimate of capacity and which one should be used as a tool to determine capacity as an input variable for traffic management on the multilane highway segment under study.

3. Methodology

3.1 Data collection

In this study, we adopted a 24-meter-long section on Phahonyothin Road, a multilane highway located in Khlong Luang District, Pathum Thani Province, Thailand, as a study area for data collection purposes. The distance between two recognized highway marks was specified as 24 m and used to replicate the mechanism behind a speed gun, which measures a vehicle's spot speed (time mean speed) by detecting its license plate between two points, typically over a short distance, and estimating the vehicle's spot speed using the velocity equation, v = s/t. This work used a video recorder to collect data; thus, the speeds of vehicles were measured using this method.

The highway section under investigation consisted of six lanes in total, three lanes in each direction, and the capacity of the southbound highway segment was the main emphasis of this study. Each lane width was 3.50 m (11.5 ft), while the shoulder width on both sides was 1.80 m (6.0 feet) each. The highway is divided by Jersey barriers (modular barriers made of reinforced concrete) as a median. Ten access points are dispersed throughout a six-mile (9.66 km) range of the highway segment. Five of the access points 1were situated within three miles (4.83 km) upstream of the data collection point, while the other five access points were positioned within three miles (4.83 km) downstream of the data collection point. The appearance of the highway section adopted as the case study is shown in Figure 1.

Figure 1 The highway segment employed as a case study

The primary existing roadway conditions, including lane width, shoulder width, number of lanes, type of median, posted speed limit, and number of access points, were thoroughly documented. Additionally, secondary parameters, such as the percentage of heavy vehicles and the percentage of motorcycles, were determined. These variables were used as input parameters for the relevant models. The capacities estimated from these models were then compared to the empirical capacity derived from the speed-flow diagram.

Traffic flow data for the case study were collected through video recordings from an elevated vantage point, at various times throughout a weekday in October 2023. These recordings were used to construct a speed-flow plot, enabling the determination of the highway capacity via the empirical method.

In total, 22,517 vehicles traversed the highway segment of interest during the six hours of the data collection period. All vehicles were categorized into three types: cars, motorcycles, and large vehicles (trucks and buses). The details of vehicle composition of the field data collected in the study area is presented in Table 2.

Table 2 Detailed vehicle composition of the field data collected in the study area

Type of vehicle	Vehicle Count (veh)	Proportion (%)
Car	21,062	93.54%
Heavy Vehicle	613	2.72%
Motorcycle	842	3.74%
Total	22,517	93.54%

3.2 Empirical method

Traffic flow data were collected over a period of 6 hours (360 minutes) and segmented into 5-minute intervals [12, 15, 21]. The goal was to obtain both data points in congested and uncongested flow conditions; thus, the data collection was attempted during 4 hours of peak period and 2 hours of off-peak period and examine if the breakdowns were found. Next, using a 5-minute interval, the data were segmented into 72 data points and plotted on a speed-flow diagram. The capacity could then be estimated, since these data points formed an observable curve on the speed-flow diagram, which contained data points in both congested and uncongested flow conditions, including breakdowns. Since a number of breakdowns were found, this meant that the data collected were sufficient for estimating the capacity. The numbers of different types of vehicles traversing the highway section (cars, motorcycles, and large vehicles, i.e., trucks and buses) were counted and converted into passenger car units (PCUs). Heavy vehicles were equivalent to 2.500 cars and motorcycles were equivalent to 0.333 cars [28]. The average vehicle speed for each 5-minute interval was then measured from the videos recorded. Each data point consisted of a vehicle flow, in PCU, and the corresponding spot speed. The spot speed, which was the estimated average speed of all vehicles passing a very short distance on a roadway over a specified time, was determined by measuring the elapsed time each vehicle traveled a distance of 24 m and dividing this distance by that travel time. The average spot speed (time mean speed estimation) of all the vehicles during each 5-minute interval was adopted to pair with the corresponding flow rate within the same interval as a datapoint in the speed-flow plot. An average spot speed (u_t) of n vehicles was calculated via equation (1), where u_i denoted the spot speed of the i^{th} vehicle [29].

$$u_t = \frac{\sum_{i=1}^{n} u_i}{n} \quad (1)$$

Subsequently, the speed-flow diagram was produced by plotting all the data points, which comprised average vehicle speed and the corresponding vehicular flow, measured in passenger car equivalent units (PCU). The empirical capacity of the highway segment was determined by measuring the average vehicle flow rate at the pre-breakdown, or the point at which the average vehicle speed was on the verge of abruptly decreasing and becoming congested [1]. A breakdown is a phenomenon when a flow of vehicles in the traffic stream encounters a sharp drop in speed and suddenly switches from an uncongested flow condition to a congested flow condition. The flow measured each time immediately prior to the occurrence of a breakdown was used to determine the average maximum flow, which is an estimation of empirical capacity [1, 13]. The speed-flow diagram of the field data collected on the highway section is displayed in Figure 2.

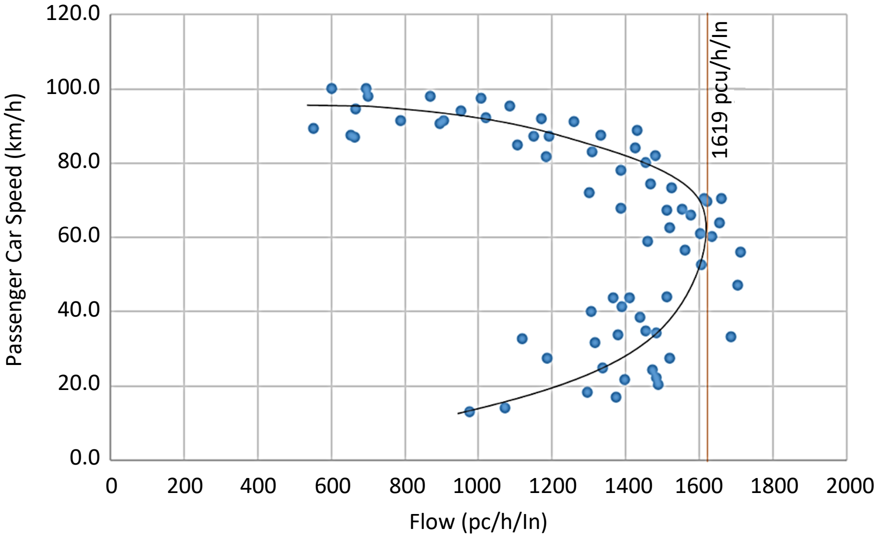

Figure 2 The speed-flow diagram based on data collected from the studied highway section

As seen in Figure 2, the empirical highway capacity was determined at 1,619 passenger car units per hour per lane, as a result of four pre-breakdowns. The estimated capacity obtained from the empirical method was found to occur at an average speed of 68.2 km/h, as shown in Table 3.

Table 3 Flow rates and the average speed observed at pre-breakdowns

Pre-breakdown	Flow per lane (pc/h/ln)	Average speed (km/h)
1	1,658	70.6
2	1,654	64.0
3	1,552	67.7
4	1,613	70.6
Average	1,619	68.2

3.3 Highway Capacity Manual 2010 model (HCM 2010 model)

Physical roadway conditions and traffic data (such as lane width, shoulder width, type of median, posted speed limit, and access point density) were used as input parameters to determine the estimated multilane highway capacity via the HCM 2010 model.

Firstly, the estimated free-flow speed (*FFS*), which is the average speed of vehicles in miles per hour measured during low-flow conditions, was determined based on equation (2).

$$FFS = BFFS - f_{LW} - f_{LC} - f_M - f_A \quad (2)$$

BFFS was the base free-flow speed, which was the base speed of traffic on an uninterrupted flow highway. *BFFS* was taken as 98.04 km/h, or 60.92 mi/h, which was the legal speed limit of the highway segment of 55.92 mi/h (90 km/h) plus 5 mph for posted speed limits of at least 50 mph.

Since the lane width was found to be 11.5 feet, the adjustment factor for lane width (f_{LW}) was interpolated at 0.95 mi/h, with regard to Table 4 [3].

Table 4 HCM's adjustment factors for lane width on six-lane multilane highways (f_{LW})

Lane width (ft)	Reduction in free-flow speed, f_{LW} (mi/h)
≥12	0.0
11	1.9
10	6.6

For the six-lane multilane highway, the adjustment factor for lateral clearance (f_{LC}) was 0 mi/h for the shoulder width of 6 feet on both sides (12 feet in total), according to Table 5 [3].

Table 5 HCM's adjustment factors for lateral clearance on six-lane multilane highways (f_{LC})

Total lateral clearance (ft)	Reduction in free-flow speed, f_{LC} (mi/h)
≥12	0.0
10	0.4
8	0.9
6	1.3
4	1.7
2	2.8
0	3.9

Next, since the highway section was divided by a physical median, the adjustment factor for median type (f_M) was 0 mi/h, based on Table 6 [3].

Table 6 HCM's adjustment factors for median type on six-lane multilane highways (f_M)

Median type	Reduction in free-flow speed, f_M (mi/h)
Undivided	1.6
Two-way turning lanes	0.0
Divided	0.0

Finally, over a distance of six miles, the road portion featured ten access points. Therefore, the adjustment factor for access points (f_A) equals 0.25 × (10/6) = 0.42 mi/h, with regard to Table 7 [3].

Table 7 HCM's adjustment factor for access points on six-lane multilane highways (f_A)

Access density (points/mi)	Reduction in free-flow speed, f_A (mi/h)
0	0.0
10	2.5
20	5.0
30	7.5
≥40	10.0

As such, according to equation (2), the estimated free-flow speed (*FFS*) = 60.92 – 0.95 – 0 – 0 – 0.42 = 59.55 mi/h (95.84 km/h).

Finally, the estimated capacity of the six-lane highway segment for the *FFS* of 59.55 mi/h was determined at a density of 45 passenger cars per mile per lane (pc/mi/ln), using the graphical approach based on HCM 2010, as shown in Figure 3 [3]. As a result, the highway capacity produced by the HCM 2010 model was approximately 2,183 pc/h/ln, or 6,549 pc/h, derived from the graphic estimation using PlotDigitizer [30], which is a tool that makes it possible to reliably extract raw data from X-Y type charts [31]. The estimated capacity obtained from the HCM 2010 model was found to occur at a predicted speed of 55.0 mi/h, or 88.6 km/h.

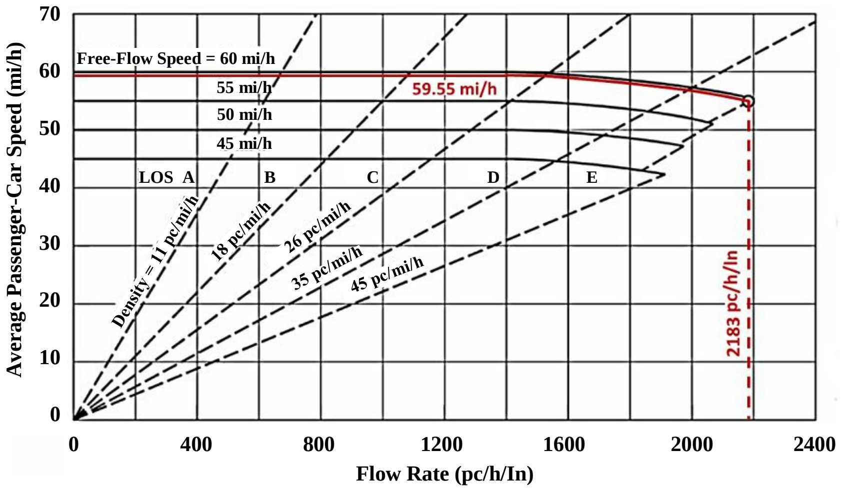

Figure 3 Speed-flow curve showing the capacity produced by the HCM 2010 method [3]

3.4 Highway Capacity Manual 2016 model (HCM 2016 model)

Generally, the HCM 2016 method for estimating multilane highway capacity is similar to the HCM 2010 method. The only difference is that the HCM 2016 model switches the step for determining the capacity via the graphical method to directly plugging in the estimated free-flow speed into an equation used to predict the capacity of the highway segment.

The calculation of capacity in this model began with the same procedure for determining the free-flow speed (*FFS*), with the same set of variables and corresponding values, as previously elaborated on in Section 3.3. Therefore, *FFS* was estimated using equation (2) and the *FFS* carried out by the equation was 59.55 mi/h, which was equal to the resultant *FFS* obtained from the HCM 2010 model.

Ultimately, the capacity was calculated by plugging in the estimated free-flow speed (*FFS*) into equation (3), where *C* denoted the estimated capacity of the segment.

$$C = 1{,}900 + 20 \times (FFS - 45) \quad (3)$$

Consequently, the estimated capacity of the highway segment using HCM 2016 (*C*) was approximately 1,900 + 20 × (59.55 – 45) = 2,191 pc/h/ln, or 6,573 pc/h in total. The estimated capacity of the model was the flow rate at which the density was 45 pc/mi/ln, as depicted in Figure 4 [4]. The estimated capacity obtained from the HCM 2016 model was found to occur at an approximate speed of 48.7 mi/h, or 78.4 km/h.

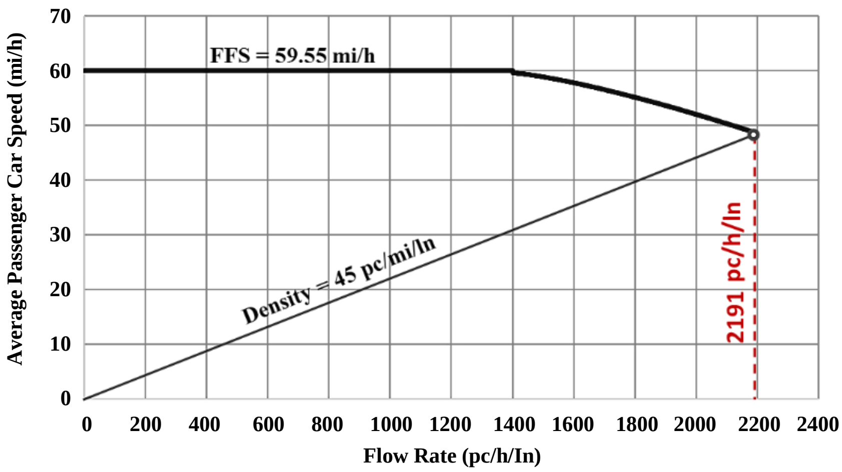

Figure 4 Speed-flow curve showing the capacity produced by the HCM 2016 method [4]

3.5 Thailand Department of Highways' model (DOH model)

The DOH's highway capacity estimation model requires the following input parameters: the number of lanes, the lane width, the shoulder width, the percentage of motorbikes and heavy vehicles, and the roadside setting. The DOH model employs a universal capacity under base conditions of 2,200 pc/h/ln, which is applicable to all types of highways, with six adjustment factors multiplying the base capacity value. These six adjustment factors are: the number of lanes (*N*), the roadside environment adjustment factor (R_I), the lane width adjustment factor (R_L), the adjustment factor for lateral clearance (R_C), the adjustment factor for two-wheeled vehicles (R_N), and the adjustment factor for the proportion of heavy vehicles (R_J). Equation (4) illustrates the model for assessing the capacity of a multilane highway using the DOH model, where *C* denotes the estimated highway capacity [5].

$$C = 2{,}200 \times N \times R_I \times R_L \times R_C \times R_N \times R_J \quad (4)$$

The model applied a universal capacity under base conditions of 2,200 pc/h/ln. First, since the highway section of interest consisted of three lanes per direction, the value of N in the equation was determined as being 3. Second, the value of R_I was 0.70 because the study area was a part of the Bangkok Metropolitan Area; otherwise, the value of R_I would be 0.90 for any other locations.

Next, the lane width (W_L) of each lane was 3.50 m; therefore, R_L was given a value of 1.00 for lane widths of at least 3.25 m. However, if the lane width was narrower than 3.25 m, equation (5) would be used.

$$R_L = \begin{cases} 1.00 & ; W_L \geq 3.25\ m \\ (0.24 \times W_L) + 0.27 & ; W_L < 3.25\ m \end{cases} \tag{5}$$

A value of R_C of 1.00 was used in the equation because the shoulder widths (W_C) on each side were greater than, or equal to, 0.75 m. However, equation (6) would be activated if the shoulder width was narrower than 0.75 m.

$$R_C = \begin{cases} 1.00 & ; W_C \geq 0.75\ m \\ (0.18 \times W_C) + 0.86 & ; W_C < 0.75\ m \end{cases} \tag{6}$$

Next, the adjustment factor for two-wheeled vehicles (R_N) was determined using equation (7), where MC denoted the percentage of motorcycles in traffic.

$$R_N = \frac{100}{100 + (0.75 \times MC)} \tag{7}$$

Since it was observed that 3.7% of all vehicles in traffic were motorcycles, the value of 3.7 was assigned for MC. Equation (7), therefore, produced a value of R_N of 0.9728.

Finally, the adjustment factor for the proportion of heavy vehicles (R_J) was obtained from equation (8), where the percentage of heavy vehicles in traffic was denoted by HV.

$$R_J = \frac{100}{\left(1 - \frac{HV}{100}\right) + \left(2 \times \frac{HV}{100}\right)} \tag{8}$$

According to the field data, the percentage of heavy vehicles to all vehicle types was 7.8%; therefore, the value of 7.8 was assigned for HV. As a result, the value of R_J was 0.9276, as mandated by equation (8).

Consequently, the capacity for the case study, estimated by using the DOH model (C) was approximately 2,200 × 3 × 0.70 × 1.00 × 1.00 × 0.9728 × 0.9276 = 4,169 pc/h, or 1,390 pc/h/ln, based on equation (4). However, the estimated speed at which the capacity occurred could not be derived from the DOH model.

4. Results and discussion

The empirical method utilizing the speed-flow diagram yields a resultant capacity of 1,619 pc/h/ln for the six-lane highway segment in this study. The result shows that the highway capacity estimated using the HCM 2010 method is 2,183 pc/h/ln, which is 564 pc/h/ln, or 34.8% greater than the empirically measured capacity using the speed-flow diagram. This finding aligns closely with the conclusions of Chaipanha et al. [25]. In comparison to the empirically observed capacity, the highway capacity calculated by the HCM 2016 technique is 2,191 pc/h/ln, which is 572 pc/h/ln higher, or 35.3% greater. On the other hand, the capacity estimated using the DOH method is 1,390 pc/h/ln, which is 229 pc/h/ln, or 14.1% lower than the empirically measured capacity. As Table 8 illustrates, the HCM 2016 model yields the greatest capacity, which is similar to the results produced by the HCM 2010 model; however, the capacities predicted via these two models overestimate the empirically measured capacity. On the contrary, the capacity derived from the DOH model is the lowest of all the models, and yet it underestimates the empirical capacity. The predicted speed at which the capacity occurs, as predicted by the HCM 2010 model, is 88.6 km/h, followed by the predicted speed of 78.4 km/h, as derived from HCM 2016, while the average speed at capacity, obtained from the empirical method, is 68.2 km/h. In contrast, the DOH model does not provide the approximate speed at capacity.

Table 8 Comparison of the capacities estimated by various methods

Method	Capacity per lane (pc/h/ln)	Compared with empirical (pc/h/ln)	Compared with empirical (%)	Corresponding speed (km/h)
HCM 2016	2,191	+572	+35.3%	78.4
HCM 2010	2,183	+564	+34.8%	88.6
Empirical	1,619	-	-	68.2
DOH	1,390	-229	-14.1%	-

The HCM 2010 method shows marginal inaccuracies in predicting capacity on the highway segment of interest, which is located in Thailand, likely due to differences in driver behavior between Thailand and the United States, as well as the higher proportion of motorcycles on Thai roadways compared to the United States. Most importantly, the HCM 2010 method does not account for the proportion of motorcycles (%MC) in its model, which may lead to discrepancies when used to estimate road capacity in Thailand. The result is similar to the findings from recent studies in Sri Lanka [17] and Malaysia [19] and shows that the HCM 2010 model may not be applicable in some countries, especially in areas where the proportion of motorcycles in traffic is substantial. In addition, the estimated speed derived from the HCM 2010 model seems to overestimate the existing speed on the multilane highway segment, as seen in Table 8.

The higher capacity estimated by the HCM 2010 model, compared to the predicted actual capacity revealed by the results of this research, is similar to the finding recommended by Chaipanha et al. [25]. On the other hand, this conclusion contradicts the findings from another study on Thai roadways, carried out by Chaipanha and Kaewwichian [27], but that research was merely conducted on two-lane rural highways, after all. However, both of these recent studies [25, 27] did not directly compare the resultant estimated capacities obtained from the HCM 2010 model to the empirical capacities measured via a speed-flow plot. Instead, microscopic traffic simulation models were applied to assume the actual capacity in both of these studies. The availability of recent and pertinent field traffic flow data is one of the key factors that has been suggested could contribute to the increased reliability of operational highway analyses [14].

Similarly, the study also reveals that the DOH model is not as accurate as it should be, as it has not been updated for over two decades and does not account for changes in driver behavior, vehicle types, and vehicle performance that have occurred over time with advancements in vehicle technology. For example, the presence of autonomous vehicles on the road could increase highway capacity [15, 32-34]. Additionally, the method does not consider the access point density adjustment factor, which can significantly impact the accuracy of capacity estimation since high numbers of access points tend to reduce the flow rate on a highway.

To ensure accurate highway capacity estimation in Thailand, it is essential to collect data and conduct comprehensive studies to update the DOH model. The data should then be statistically analyzed using state-of-the-art techniques, such as machine learning [35] and deep learning [36], to develop a set of equations or a new methodology that systematically relates highway capacity to various factors. The study should encompass a range of additional factors not yet included in the model. These additional factors could include: median type [3, 4]; weather conditions, whether it is clear, rainy, or foggy [10, 21]; side friction, such as pedestrian movements and access points [37]; time of day, whether it is daytime or nighttime, since illuminance may affect operating speed and awareness [38, 39]; terrain type [21], e.g., flat, rolling, or mountainous; and the proportion of autonomous vehicles in traffic [15, 32-34].

Additionally, the results of this study show that the approximated speeds at which capacity occurs, as predicted by the HCM 2010 and HCM 2016 approaches, were substantially higher than the average speed at capacity obtained from the empirical method. The underlying reason for this is that the free-flow speeds recommended in these HCM methods might be different from the actual free-flow speeds on the multilane highway segment in this case study. This finding suggests potential discrepancies in driver behavior between Thai and American drivers, as well as differences in traffic flow characteristics on highways in the United States and Thailand, where the market penetration rate of motorcycles is significant.

5. Conclusions and future work

This study concludes that, for the multilane highways segment in this case study, adopting the HCM 2010 and HCM 2016 models may lead to overestimated capacities, whereas applying the DOH model may underestimate the capacities. The findings show that the HCM 2010, the HCM 2016, and the DOH methods still have some margins of error when they are used to estimate the capacity of the multilane highway.

The evolution of driver behavior, traffic flow characteristics, vehicle types, and vehicle performance over time, as a result of advancements in vehicle technology, may have an impact on the accuracy of capacity assessment via the DOH model because it has not been updated for more than two decades. In addition, the accuracy of capacity estimation using the DOH model can be improved if it takes into account access point density, as well as additional factors such as weather [10, 21], time of day [38, 39], terrain type [21], median type [3, 4], and proportion of self-driving vehicles [15, 33].

Due to differences in driver behavior between Thai and American drivers, and the absence of a percentage of motorcycle riders in both the HCM 2010 and HCM 2016 approaches, using them to predict the capacity of the highway segment of interest can produce an overestimated result. Furthermore, speeds at the capacities estimated via the HCM 2010 and HCM 2016 models do not accurately reflect the pre-breakdown speeds empirically measured on the multilane highway segment, which is located in Thailand.

Therefore, we advise that a nationwide study be carried out by the Thailand Department of Highways, to cover a variety of road types and locations in Thailand. To increase the accuracy of capacity estimation, it is possible to separately develop a capacity estimation model for each type of highway facility, such as an expressway, multilane highway, two-lane undivided highway, and roundabout, rather than using a universal model for all types of facilities. Each model should be developed using big data collected from highways with combinations of different characteristics to perform sensitivity analyses (i.e., it should be conducted based on various lane widths, lateral clearances, median types, terrains, weather conditions, times of day, access points, and vehicle compositions). Additionally, traffic data should be gathered from various locations throughout the country, to check whether driver behavior in different regions affects the accuracy of capacity estimation. These models could be created using state-of-the-art techniques, such as machine learning or deep learning, to develop procedures or speed-flow curves for various types of traffic facilities. Future studies should also reinvestigate the DOH's highway capacity estimation model by using various types of highways with different characteristics, in order to confirm whether any revisions to the model are necessary to improve its accuracy. The next attempt should also consider the evolving conditions and factors influencing highway capacity [15, 32-34]. Addressing these limitations will be the focus of the authors' future research.

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