

Passenger Car Equivalent Estimation Methods at Urban Signalized Intersections: A Systematic Review

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Abstract

This study presents a systematic review of Passenger Car Equivalency (PCE) at signalized intersections. The review focuses on comparing PCE calculation methods, examining PCE values across methods, and identifying the key influencing factors. Following the PRISMA methodology, 40 relevant studies were identified. The analysis revealed several critical calculation factors, including road geometry and vehicle composition. These studies employed seven major methods for PCE estimation: (1) headway ratio, (2) regression, (3) delay-based, (4) area occupancy, (5) queue-based, (6) capacity-based, and (7) optimization (Theil's Coefficient). The findings indicate that PCE values vary substantially across studies, with motorcycle values ranging from -1.056 to 1.02 , three-wheeler values from 0.22 to 1.51 , and heavy vehicle values from 1.13 to 5.06 . Cross-study comparisons revealed that this variation exists not only between countries but also between cities within the same country. This variability is attributed to traffic volume, traffic composition, approach width, and differences in driver behavior. The results support treating PCE as a dynamic parameter rather than static, as fixed values from national guidelines may not adequately represent local traffic conditions.

Keywords: Passenger Car Equivalent (PCE); Passenger Car Unit (PCU); signalized intersections; saturation flow; headway; mixed traffic conditions; urban intersection capacity; systematic review

1. Introduction

The traffic flow at urban signalized intersections is fundamentally complex due to the presence of a variety of vehicles with different static and dynamic characteristics. Each vehicle type occupies varying road spaces, operates at different speeds, and exhibits distinct acceleration characteristics, which collectively influence saturation flow, queue discharge patterns, and overall performance of the intersections [1]. Consequently, effective regulation of traffic flow at signalized intersections is one of the most critical challenges for urban network performance. In this context, accurate capacity estimation is essential for efficient intersection design and signal management. The lack of reliable estimates leads to oversaturated conditions, excessive delays, and network-wide congestion. While capacity estimation is relatively straightforward for homogeneous traffic streams, it becomes particularly challenging under heterogeneous conditions where motorcycles, auto-rickshaws, buses, trucks, and passenger cars share the same roadway [2].

The Passenger Car Equivalent (PCE), also referred to as the Passenger Car Unit (PCU), is a conversion factor that quantifies the differing impacts of various vehicles on the free-



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flowing movement of traffic by relating each type of vehicle to a standard passenger car [3,4]. This standardization enables traffic engineers to apply conventional capacity estimation procedures developed for homogeneous conditions of traffic streams with varying proportions of vehicle types.

The concept of PCE has evolved considerably since its introduction in the mid-20th century. Early studies by Webster [5] and Miller [6] established methods to quantify how different vehicles impact the capacity of an intersection. Early approaches, such as Webster's method, relied on controlled track experiments to establish equivalency factors based on the relationship between vehicle counts and saturation flow rate (SFR) [7]. Since then, later researchers have investigated signalized intersection-specific characteristics such as how queues are discharged, start-up lost time, and saturation headways [8,9]. At signalized intersections, SFR is a representation of the highest possible discharge rate during the green phase under given geometric and traffic conditions and the accurate determination of SFR depends on appropriate PCE values that reflect local vehicle characteristics, driver behavior, and traffic composition [2,7].

The Highway Capacity Manual (HCM) provides standard PCE values, which are based primarily on traffic conditions in North America, where lane-based movements and relatively homogeneous vehicle fleets are typical [10]. In addition to the HCM, other National Guidelines, such as the Indonesian Highway Capacity Manual (IHCM 1997) and the Indian Roads Congress (IRC) Specifications also provide values that are specific to each region, but the data provided may not accurately represent the complexities associated with modern day urban traffic patterns [11,12]. The limitations become even greater when considering that the behavior of drivers including start-up response time, gap acceptance, and aggressiveness varies greatly across countries and regions due to cultural and socio-economic differences [13,14]; therefore, the direct transfer of PCE values between different traffic environments is not straightforward and remains problematic [15].

Estimation of PCE at signalized intersections has attracted researchers over several decades. Studies have shown that PCE values are not static parameters but vary depending on a range of contextual factors. For instance, different proportions of motorcycle, large vehicle, and middle-sized vehicle traffic types can significantly affect vehicle interaction in traffic streams, thereby affecting PCE values [16]. Another major influence is roadway geometry. Factors such as the approach width, the number of lanes, and turning movement configurations all have an effect upon the way drivers behave and thus their equivalent relationship [17,18]. Non-lane-based traffic movement is common in many areas around the world, particularly across Asia. This pattern creates complex lateral interactions between vehicles that are difficult for lane-based models to accurately estimate [19,20]. To address these challenges, researchers continue to develop alternative approaches, including area occupancy methods, simulation-based techniques, and dynamic PCE formulations that account for varying traffic conditions [21,22].

Research on Passenger Car Equivalent (PCE) values at urban signalized intersections has generated a rich and diverse set of findings; however, these contributions are dispersed across different methodological approaches, traffic conditions, and geographic settings, making it difficult to draw generalizable conclusions. Therefore, several gaps remain in the current understanding of PCE values at urban signalized intersections. First, there has been no systematic review to provide a comprehensive overview of how the results from the various methodologies are categorized and compared, which limits the extent to which we can develop generalized conclusions. Second, the large variation in reported estimations for similar vehicle types and traffic conditions raises many questions regarding what causes the differences and the potential consequences of this for future applications.

Third, the extent to which PCE values developed in a given context are transferable to other geographic or traffic environments is not well understood.

This systematic review directly addresses these gaps by offering a comprehensive synthesis of existing research on Passenger Car Equivalent (PCE) values at urban signalized intersections. This study was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [23] and provides a complete synthesis of available PCE estimation methodologies, reported PCE values across vehicle types and geographic regions, and key factors affecting PCE variability. This review represents the first comprehensive assessment of PCE estimation at signalized intersections and establishes a robust foundation for both methodological advancement and evidence-based practice.

The remainder of this paper is organized as follows. In the literature, the terms Passenger Car Equivalent (PCE) and Passenger Car Unit (PCU) are both used to represent the same concept of quantifying heterogeneous traffic streams into an equivalent passenger car-based unit. The term PCE is more commonly referenced in North America using conventional guidelines from the Highway Capacity Manual, while PCU is generally more widely used in Britain, Australia, and Asia. Both terms appear in studies included in this review; for clarity and consistency, this manuscript uses the term PCE throughout. Section 2 presents an overview of fundamental PCE concepts and the evolution of estimation approaches in the literature. Section 3 describes the review methodology, including the search strategy, study selection process, and data extraction procedures. Section 4 reports the results, covering publication trends, geographic distribution of studies, methodological classifications, and synthesized PCE values. Section 5 discusses the findings and their implications for research and practice, limitations, and recommendations for future research.

2. Background and Related Works

Estimating PCE at signalized intersections has several characteristics different from those of uninterrupted-flow facilities. Highway segments are subject to a primary type of interaction among vehicles (car-following) whereas signalized intersections have numerous types of interactions, namely queue formation, start-up acceleration, and signal-constrained discharging patterns. As a result, many researchers have developed specific methods for estimating PCE at intersections which account for factors related to the saturation flow rate and lost time at an intersection as well as the spatial relationships of the approach geometries. The challenge becomes substantially more complex in heterogeneous traffic environments, where vehicles with different physical dimensions and performance characteristics share the same roadway without strict lane discipline, necessitating methods that can capture both temporal and spatial aspects of vehicle interactions. Over the past five decades, these complexities have driven the development of multiple methodological approaches, each attempting to capture these dynamics from different perspectives.

The formal incorporation of PCE into traffic engineering practice occurred with the 1965 Highway Capacity Manual (HCM), which introduced this concept to account for the impact of buses and trucks on traffic flow at signalized intersections [24]. Since then, various methodologies have been developed for estimating PCE values at signalized intersections, each offering different theoretical perspectives on how vehicle equivalency should be measured and quantified.

2.1. Methodological Approaches for PCE Estimation

Seven primary methodological families have emerged for estimating PCE values at signalized intersections. These methods are presented below in chronological order of their development, illustrating how each approach emerged to address limitations of earlier

methods: headway-based methods (1947–1965) provided the first systematic framework for quantifying vehicle equivalency; regression-based methods (1978) enabled PCE estimation from aggregate vehicle counts without requiring individual headway measurements; delay-based methods (1984) shifted focus from capacity consumption to operational performance impacts; area occupancy methods (2003) introduced a two-dimensional perspective to capture lateral vehicle positioning in non-lane-based traffic; optimization-based methods (2011) addressed the circular dependency between PCE and saturation flow through iterative algorithms; capacity-based methods (2014) utilized microsimulation to compare throughput under controlled conditions; and queue-based methods (2017) derived PCE values directly from queue discharge characteristics. Additionally, alternative methodologies are discussed below. Each methodology is described by its theoretical basis, mathematical formulation, and application in various traffic conditions.

2.1.1. Headway Ratio Method

The headway ratio method is the most widely used approach for estimating Passenger Car Equivalent (PCE) values at signalized intersections. A major theoretical advantage of the headway ratio method is its direct connection between time headway and saturation flow rate. Webster [5] has formally established the relationship between saturation flow rates and time headways, which have been utilized to determine the most effective timing for traffic signals, establishing that the saturation flow rate is the reciprocal of the average saturation headway as shown in Equation (1):

$$S = \frac{3600}{\bar{h}} \quad (1)$$

where

- S is the saturation flow rate in vehicles per hour of green (veh/hg),
- $\bar{h}$ is the average saturation headway in seconds.

The relationship has been used by the Transportation Research Board in its Highway Capacity Manual [25] as the conceptual framework for utilizing headway ratios to estimate the impact on capacity. A vehicle will consume additional green time in each cycle when it has an increased headway; consequently, fewer vehicles will be able to leave during each cycle. Therefore, PCE is utilized to determine the degree to which a vehicle impacts capacity compared to a standard passenger vehicle.

Time Headway Measurement

The headway ratio method is based upon an important principle regarding the relationship between PCE and time headways. Time headway is defined as the time between successive vehicles crossing a reference point. In this context, it is defined as the difference in time between the front or rear bumper of the leading vehicle and the corresponding bumper of the trailing vehicle when they cross the stop line. Time headways are defined by Pline [26] in the Traffic Engineering Handbook as “the time interval between two successive vehicles at a fixed point.” Time headways can be calculated using Equation (2):

$$h_i = t_2 - t_1 \quad (2)$$

where

- h_i = Time headway (s) for all vehicle types (mini-bus, bus, truck, pickup, and SUV).
- t_1 = The time at which the front bumper of the first vehicle (the vehicle type under consideration) crosses the stop line.

- t_2 = The time at which the front bumper of the following vehicle (which is always assumed to be a passenger car) crosses the stop line.

To determine the average headway using Equation (3), all the collected field data were grouped by vehicle type and intersection. The time headways were calculated using Excel and then the average time headways were found by dividing the total of the headway differences ($t_2 - t_1$) by the total number of observations (n):

$$\text{Average time headway} = \frac{\sum(t_2 - t_1)}{N} \quad (3)$$

Basic PCE Formulation

The headway ratio method originated from the work of Greenshields et al. [27], who developed what has come to be known as the ‘basic headway method’ and derived PCE values based on the analysis of discharge headways and have been used by Greenshields et al. [27], Scraggs [28], Webster [5], and Miller [6]. As shown in Equation (4), the headway ratio method expresses PCE as the ratio of the average headway of a vehicle type to that of passenger cars:

$$PCE_i = \frac{\bar{h}_i}{\bar{h}_c} \quad (4)$$

where

- PCE_i is the Passenger Car Equivalent for vehicle class i ,
- $\bar{h}_i$ is the average headway of vehicle class i , and
- $\bar{h}_c$ is the average headway of passenger cars.

The 1965 HCM used the basic headway method to set the PCE value for trucks at 1.85. This value has been revised in subsequent editions of the HCM: 1.5 in 1985, 2.0 in 1994 and 1997, 1.5 in 2000, 2.0 in the 2010 edition, and 2.0 in the most recent 2022 edition [10,25,29–31]. This fluctuation reflects the ongoing uncertainty regarding the existence of a single appropriate value that would represent the diverse truck population.

Although the headway ratio method provides an easily understood and simple way to estimate PCE, its reliance on individual vehicle headway measurements presents practical challenges in heterogeneous traffic conditions where lane discipline is weak or absent. This limitation motivated the development of alternative approaches that could estimate PCE values from aggregate traffic data without requiring detailed headway observations.

2.1.2. Regression-Based Method

Regression-based methods are one of the most widely recognized alternatives to the headway ratio-based methods for determining Passenger Car Equivalent (PCE) values at Signalized Intersections. The Transport and Road Research Laboratory developed Road Note 34 [32], which specified a process for saturated flow measurement via vehicle classifications and time interval measurements. However, these methods require vehicle classification equivalents (PCEs) to be assumed rather than calculated directly from the data [7].

Branston and van Zuylen [33] developed a regression-based method to eliminate the need to assume PCEs, estimating PCE values and saturation flow simultaneously using saturated green time as the dependent variable and the number of vehicles crossing the stop line as independent variables. One of the primary advantages of the regression method is that it does not require measurement of individual vehicle headways and therefore can be applied to heterogeneous traffic conditions where lane discipline does not exist. They modeled the relationship between the amount of each type of vehicle passing the stop bar in a given counting period and the time it takes to clear the stopping area using a linear

equation. The ratio of vehicle coefficients produces the PCE value, while the intercept of the model represents the start-up lost time. This regression approach was later applied by Branston and Gipps [34] for measuring lost time and saturated flow.

Branston and van Zuylen [33] determined there were two different ways of conducting counts, depending upon Haight's [35] terminology for synchronous and asynchronous counts. The key differences between the synchronous and asynchronous counting methods lie in the termination of the counting periods.

Kimber et al. [7] have carried out a systematic comparison of the two methods and found that the synchronous method produces estimates that are closer to those of true PCE values obtained from headway ratio method. In contrast, the asynchronous method estimates systematically lower PCE values. Therefore, the majority of studies in the literature prefer the synchronous counting method [36–38].

Synchronous Regression Method

In the synchronous counting method, counting periods begin when a vehicle passes the stop line and end when the next vehicle passes. In this approach, each counting period contains an integer number of vehicles, and the period duration depends on vehicle passage times. The dependent variable is time (T), while vehicle counts serve as independent variables.

Branston and van Zuylen [33] proposed the following Equation:

$$T = \delta_1 \lambda_1 - \delta_2 \lambda_2 + \eta_1 X_1 + \eta_2 X_2 + \dots + \eta_n X_n + \varepsilon \quad (5)$$

where

- T (or τ): Length of counting period (dependent variable).
- δ_1 : Dummy variable: 1 if period begins at green light, 0 otherwise.
- δ_2 : Dummy variable: 1 if period ends at amber light, 0 otherwise.
- λ_1 : Green start lag (start-up lost time).
- λ_2 : Green end lag.
- η_i : Average headway of vehicle type i .
- X_i (or n_i): Number of vehicles of type i crossing stop line.
- ε : Error term.

Asynchronous Regression Method

In the asynchronous counting method, counting periods occur at fixed time intervals (e.g., 6 s) and are independent of vehicle passages. Since the time interval is held constant, T cannot serve as the dependent variable. Therefore, the equation is rearranged so that passenger car count (n_1) becomes the dependent variable [7,33]. In this case, fractional vehicle counts can be obtained in a period (e.g., if a vehicle passes midway through a period, it is counted as 0.5). This fractional counting is one reason why the asynchronous method tends to systematically underestimate PCE values [7].

Branston and van Zuylen [33] proposed the following equation for the asynchronous method:

$$X_1 = -\sigma \lambda_1 \delta_1 + \sigma \lambda_2 \delta_2 - \alpha_2 X_2 - \dots - \alpha_n X_n + \sigma T + \varepsilon \quad (6)$$

where

- X_1 = number of passenger cars (dependent variable).
- $X_2, \dots, X_n$ = counts of other vehicle types (independent variables).
- σ = saturation flow rate per passenger car ($1/\eta_{car}$).
- $\alpha_2, \dots, \alpha_n$ = PCE values for other vehicle types.

- λ_1 = start-up lost time at green onset.
- λ_2 = gained time at green termination.
- δ_1 = dummy variable; 1 if period includes green onset, otherwise 0.
- δ_2 = dummy variable; 1 if period includes green termination, otherwise 0.
- T = fixed counting interval (seconds).
- ε = error term.

While regression-based methods effectively resolved the challenges associated with collecting headway data, both approaches share a common limitation. They focus primarily on the capacity consumed by individual vehicles at the stop line, without fully capturing the cumulative impact that different vehicle types impose on the entire traffic stream. Consequently, this limitation motivated researchers to explore delay as an alternative measure of vehicle equivalency.

2.1.3. Delay-Based Method

Travel time delay-based PCE estimation approaches are based on the assumption that the capacity reducing effect of heavy vehicles is directly related to the additional delay caused by these vehicles. Among the pioneers of this approach, Keller and Saklas [39] estimated PCE values as the ratio of total travel times of heavy vehicles to passenger vehicles through urban networks using the TRANSYT/7N [40] macroscopic simulation model. This study developed due to the criticism that commonly used headway-based methods only consider the excess headway consumed by heavy vehicles and do not take into account all the delays that heavy vehicles generate to the overall traffic stream. In this approach, PCE is calculated as the ratio of total travel time of vehicle type k to the total travel time of the base vehicle (passenger car). This method is based on three components: uniform delay, random delay, and running time.

Uniform Delay

Uniform delay is defined as the entire amount of time spent by a vehicle while not traveling at the free-flow speed. Figure 1 illustrates the speed profile of a vehicle approaching a signalized intersection, showing how uniform delay encompasses the deceleration, queuing, and acceleration phases. Its formation can be explained as follows:

- No exit flow when the signal is red $\rightarrow$ the queue begins to build up (uniform delay begins).
- During the transition to green, the queue continues to build up during the start-up delay period.
- Then, the queue begins to clear at the saturation flow rate.
- Incoming vehicles join the end of the queue, but since the exit speed is higher than the entry speed, the queue decreases.
- When the queue is completely cleared, exit speed equals entry speed (end of uniform delay).

TRANSYT computes uniform delay as shown in Equation (7):

$$d_u = C \cdot \sum \frac{m_t}{N} \quad (7)$$

where

- d_u is uniform delay in veh-sec/cycle,
- C is cycle length in seconds,
- m_t is queue length during interval t in vehicles, and
- N is number of steps in the cycle.

The number of vehicles in the queue is given by Equation (8):

$$m_t = \max[(m_{t-1} + y_t - z_t), 0] \quad (8)$$

where

- y_t represents inflow during interval t , and
- z_t represents outflow during interval t .

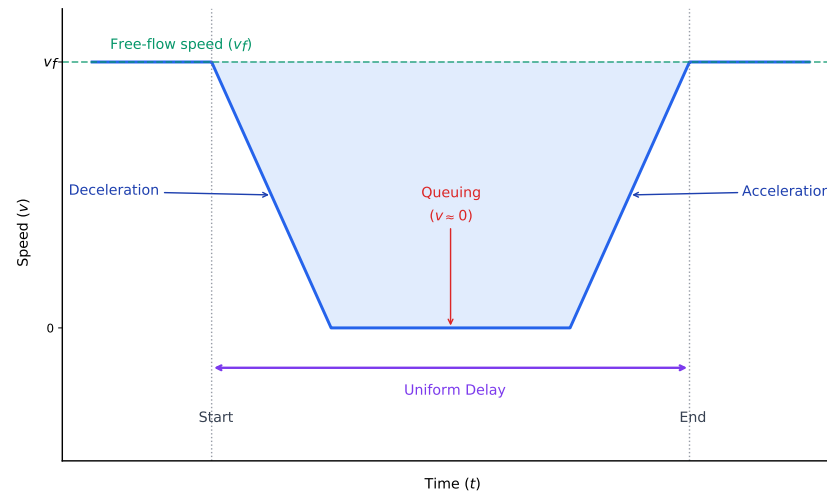


Figure 1. Uniform delay components: time spent below free-flow speed (v_f) including deceleration, queuing, and acceleration phases (based on Keller and Saklas [39]).

Random Delay

Random delay is the portion of delay that is stochastic in nature. Unlike uniform delay, which is deterministic and results from signal timing, random delay arises from the inherent randomness in vehicle arrival patterns. Figure 2 illustrates the difference between theoretical uniform arrivals and actual random arrivals, showing how vehicle clustering and gaps contribute to random delay, and Table 1 summarizes the differences between uniform delay and random delay. At lower volumes, uniform delay is more significant, but at higher volumes, random delay becomes the dominant factor [39].

Keller and Saklas [39] noted that TRANSYT uses a formulation similar to the Webster [41] model, but corrected it so that it will not break down when the saturation reaches 100% (Equation (9)):

$$d_r = \frac{15T}{S} \left\{ q - S + \left[(q - S)^2 + 240 \frac{q}{T} \right]^{1/2} \right\} \quad (9)$$

where

- d_r is random delay in veh-s/cycle,
- q is traffic volume in veh/s/cycle,
- S is saturation flow rate in veh/s of green, and
- T is simulation time in minutes.

Running Time

Running time is the third component in travel time-based delay model. It represents the duration during which a vehicle actually travels at free-flow speed. It is the portion of total travel time when the vehicle is not experiencing any delay. The relationship between these components is expressed in Equation (10) [39]:

$$TT = TR + d_u + d_r \quad (10)$$

where TT is total travel time, TR is running time, d_u is uniform delay, and d_r is random delay.

Running time and uniform delay are mutually exclusive and together account for the deterministic portion of total travel time.

Delay-based methodologies above also rely on a fundamentally one-dimensional model of traffic flow; however, in developing countries, the behavior of traffic is often two dimensional, i.e., vehicles occupy various longitudinal positions and small vehicles filter through gaps created by large vehicles. Thus, to more accurately represent these interactions, area occupancy methodologies were developed to specifically consider the spatial aspects of vehicle interactions.

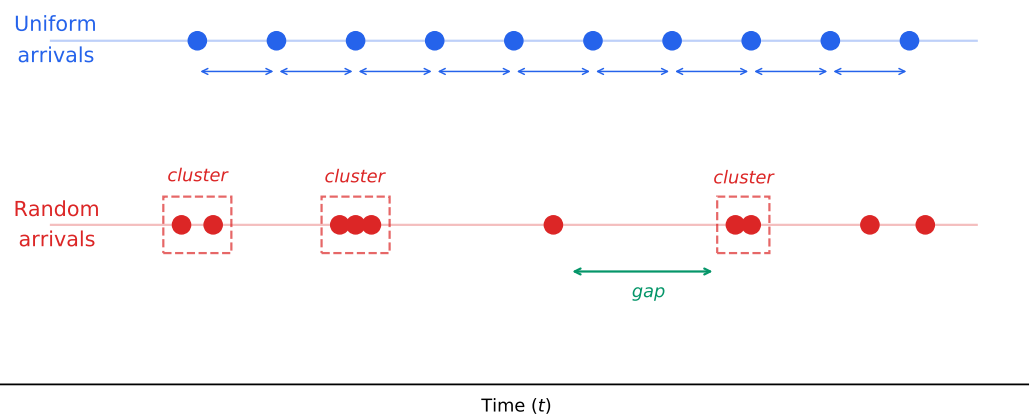


Figure 2. Comparison of uniform and random vehicle arrival patterns at a signalized intersection. Under uniform arrival assumptions, vehicles arrive at equal time intervals. In reality, traffic exhibits stochastic variations characterized by clustered arrivals and irregular gaps.

Table 1. Differences between uniform delay and random delay.

	Uniform Delay	Random Delay
Source	Signal timing (deterministic)	Random fluctuations in traffic flow (stochastic)
When does it occur?	In each cycle, when the signal is red	When the volume approaches capacity
Predictability	Predictable, exact value	Random, probabilistic, expected/mean value
When is it dominant?	Low volumes	High volumes

2.1.4. Area Occupancy Method

Area Occupancy Methods represent a fundamentally different approach to estimating PCE compared to the Headway Ratio Method. While headway-based approaches assume that traffic flows down a single dimension, lane by lane, with each vehicle following another in a straight line, area occupancy methods recognize that traffic is heterogeneously distributed over the two dimensions of road space; vehicles of all sizes occupy the roadway both laterally and longitudinally [18]. This conceptual model is especially suitable for developing countries where poor lane discipline and the number of small vehicles create very complex spatial patterns on the roadway [42].

The theoretical foundation for this approach was established by Chandra and Kumar [18] who stated that the Passenger Car Equivalents (PCEs) of a particular vehicle type should take into account its size (length and width) and how fast it travels compared to the standard passenger car. The fundamental premise of this PCE definition recognizes that the effect of a vehicle on traffic flow does not depend solely on its length as used in headway-based

methods; it depends on the total space on the road occupied by the vehicle while moving. The total space is the projected rectangular area of the vehicle on the surface of the road which is a function of vehicle length and width [43].

The concept was further developed by Arasan and Dhivya [42]. They argued that for non-lane-based traffic (i.e., “mixed traffic”), the lateral position occupied by vehicles can vary depending upon the density and composition of traffic. This point of view has led to the creation of dynamic PCE assessment techniques that consider real time traffic conditions versus static conversion ratios [44].

Approaches and Formulations

The area occupancy method has been expressed in many different forms. The fundamental equation relating speed ratio to area ratio is presented in Equation (11) by Chandra and Kumar [18]. The formulation is based on the idea that lower-speed vehicles create higher levels of impedance per unit area while larger vehicles use up more physical space to move.

$$PCE_i = \frac{V_c}{V_i} \times \frac{A_i}{A_c} \quad (11)$$

where

- V_c = mean speed of passenger cars (km/h).
- V_i = mean speed of subject vehicle type i (km/h).
- A_c = projected rectangular area of passenger car (m^2).
- A_i = projected rectangular area of subject vehicle type i (m^2).

Alex and Isaac [44] developed a simulation-based approach using modified area occupancy ratios derived from the TRAFFICSIM microsimulation model [17]. The area occupancy is calculated using Equation (12) as given by Arasan and Dhivya [42]. In the traditional approach, the area occupancy of different vehicle types is compared directly with each other, whereas in this study, the area occupancy of different vehicle categories is compared with the area occupancy of vehicles under 100% automobile traffic conditions with the same stream speed.

$$Area\ occupancy = \frac{\sum_{i=1}^n a_i t_i}{AT} \quad (12)$$

where

- a_i = projected area of vehicle i within the measurement zone (m^2).
- t_i = duration for which vehicle i occupies the measurement zone (s).
- A = total area of the measurement zone (m^2).
- T = observation period (s).
- n = total number of vehicles passing through the measurement zone.

$$PCE = \frac{\text{Equivalent area occupancy of vehicle type}}{\text{Equivalent area occupancy of car under 100\% car condition}} \quad (13)$$

Other researchers recognize that travel time at an intersection may be a more appropriate measure of impedance than speed alone; therefore, travel time–area formulations (Equation (14)) were employed by Mavani et al. [45] and Bhatt and Patel [46] that account for vehicles’ acceleration, deceleration, stop delays, and their ability to maneuver when traveling through the intersection.

$$Dy.PCE = \frac{TT_i}{TT_c} \times \frac{A_i}{A_c} \quad (14)$$

where

- TT_i = travel time of subject vehicle type i (s).
- TT_c = travel time of passenger car (s).
- A_i = projected rectangular area of subject vehicle type i (m^2).
- A_c = projected rectangular area of passenger car (m^2).

Patel and Dhamaniya [47] introduced the time occupancy approach, which incorporates delay as an indirect measure through clearance time (the time required for a vehicle to clear an intersection) (Equation (15)). Larger vehicles such as buses, trucks, and light commercial vehicles (LCVs) have reduced maneuverability in mixed traffic conditions; therefore, they cannot clear the intersection as fast as smaller vehicles, resulting in higher occupancy times and consequently higher PCE values with greater variability.

$$PCE_s = \frac{T_s}{T_p} \times \frac{A_p}{A_s} \quad (15)$$

where

- T_s = average clearing time of subject vehicle during saturated green time (s).
- T_p = average clearing time of passenger car during saturated green time (s).
- A_p = projected rectangular area of passenger car (m^2).
- A_s = projected rectangular area of subject vehicle (m^2).

A methodological concern for area occupancy models (and most other PCE estimation methods) is the circular dependency between the two parameters (PCE and saturation flow), which is required to calculate each. Some researchers have addressed this through optimization techniques that estimate both parameters simultaneously with iterations.

2.1.5. Optimization-Based PCE Method (Theil's Coefficient)

The fundamental principle of the optimization method is to minimize the difference between observed discharge flow and an ideal saturation flow profile [2,48]. The Highway Capacity Manual describes an idealized flow rate that increases to a peak (the saturation flow) at which point it decreases linearly [25]. Due to irregular queuing patterns, lack of adherence to lane discipline, and variability in vehicle size, heterogeneous traffic does not typically follow the described idealized flow rate [2]. The goal of the optimization methodology is to identify PCE values that will allow the transformation of the observed heterogeneous flow rate into an equivalent homogeneous flow rate [48].

Mathematical Formulation

The optimization problem uses Theil's coefficient as the objective function [49]. The formulation is expressed as in Equation (16) [2,48]:

$$\text{Minimize } z = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (S_b - S_i^e)^2}}{\sqrt{\frac{1}{N} \sum_{i=1}^N (S_b)^2 + \frac{1}{N} \sum_{i=1}^N (S_i^e)^2}} \quad (16)$$

where

$$S_i^e = \sum_{j=1}^k n_j \cdot p_j \quad (17)$$

subject to

$$p_j \geq p_{j,min} \quad (18)$$

where

- z represents Theil's coefficient,

- S_b is the base saturation flow (PCE/hour) adjusted to road width,
- S_i^e is the estimated saturation flow for time interval i ,
- N is the total number of time intervals,
- n_j is the number of vehicles of type j ,
- p_j is the PCE value of vehicle type j , and
- k is the number of vehicle categories.

Theil's coefficient ranges from 0 to 1, where values closer to zero indicate better agreement between observed and ideal flow profiles [49]. The coefficient provides a normalized measure of prediction error, making it suitable for comparing flows across different magnitudes [2].

The computation of optimum PCE values follows an iterative procedure [2]:

1. Initialize all PCE values to 1.0.
2. Remove non-saturated portions and compute saturation flow using current PCE values.
3. Solve the optimization formulation to obtain new PCE values that minimize Theil's coefficient.
4. Compare old and new PCE values. If convergence of values occurs, stop; otherwise, return to Step 2.

The iterative process continues until successive PCE values converge, typically within 5–6 iterations [2].

The optimization method addresses the circular dependency problem using field data through iterative algorithms. Some researchers, however, have utilized simulation environments to bypass this challenge entirely. Microsimulation enables the creation of homogeneous traffic streams composed entirely of a single vehicle type, a condition impossible to observe in real-world traffic. This method allows direct capacity comparisons between vehicle types.

2.1.6. Capacity-Based PCE Method

In the capacity-based method, PCE values are calculated as the ratio of vehicles passing the same intersection in the same time period. This approach is founded on the assumption that the capacity-reducing effect of heavy vehicles can be directly measured through outputs [50,51]. The inverse relationship between headway and capacity forms the basis of the capacity-based methodology.

Although the mathematical formulation of the two methodologies (capacity and headway) are the same, the methodologies use different measurements to calculate PCE values: the capacity-based method relies on the total number of vehicles while the headway-based method measures individual vehicle headways.

Another critical distinction is that while the headway ratio method can be utilized in either field or simulated environments, the capacity-based method can only be applied in simulated environments because it requires a uniform flow stream (e.g., 100% passenger car stream or 100% heavy vehicle stream). The PTV VISSIM microscopic simulation program is used for capacity-based PCE calculations [50,51].

The delay–volume relationship identifies capacity limitations. If a delay exceeds the duration of the signal cycle and if the average stop per cycle exceeds one, then this means the maximum number of vehicles that can pass through the intersection has been reached [51]. Beyond this point, queues exceed their critical length and congestion develops.

Mathematical Formulation

The capacity-based PCE calculation is expressed by Equation (19) [51]:

$$PCE_i = \frac{Q_{car}}{Q_i} \quad (19)$$

where

- Q_{car} = Number of passenger cars passing through the intersection per unit time (veh/h).
- Q_i = Number of vehicle type i passing through the intersection per unit time (veh/h).

$$PCE = \frac{Q_{car}}{Q_i} = \frac{3600/h_{car}}{3600/h_i} = \frac{h_i}{h_{car}} \quad (20)$$

The relationship between headway and capacity (Equation (20)) demonstrates the theoretical consistency of the capacity-based method.

The capacity-based method's reliance on simulation to generate homogeneous traffic streams limits its direct applicability to field conditions. Queue-based methods offer an alternative that derives PCE values from observable queue discharge characteristics in real world heterogeneous traffic, without requiring baseline measurements from car only queues.

2.1.7. Queue-Based Methods

Mohan and Chandra [52] identified that the saturation flow rate needs PCE values to convert the mixed traffic to homogeneous flow, whereas PCE estimation requires an accurate saturation flow measurement. Under heterogeneous traffic conditions, this circular dependency issue becomes problematic, as it is practically impossible to obtain a queue that consists entirely of passenger cars to establish baseline saturation flow rate determination.

Queue Clearance Rate Method

The queue clearance rate (QCR) method, originally developed for unsignalized intersections, was later adapted by Mohan and Chandra [52] for signalized intersection applications. This methodology assumes that the total time required for a queue to completely leave the conflict zone (Figure 3) will indicate the impact of its composition on intersection capacity.

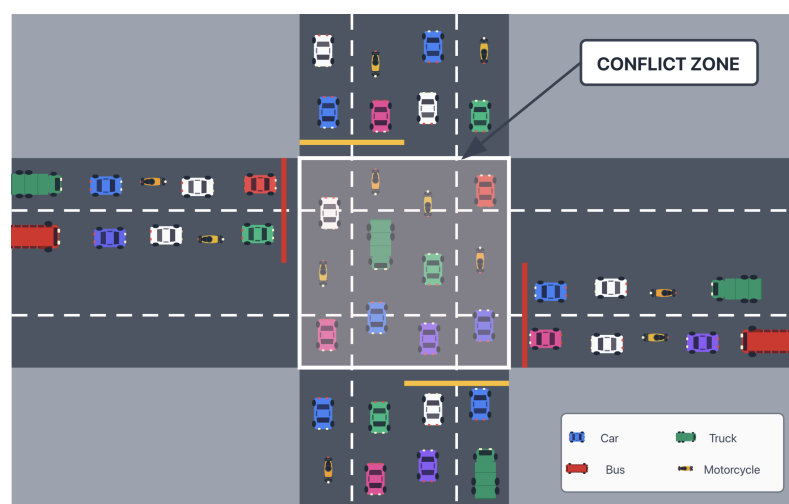


Figure 3. Schematic representation of a signalized intersection with mixed traffic flow showing the conflict zone.

The QCR method requires specific data collection protocols. There must be a clear definition of the conflict area for it to be used appropriately, with it generally being defined

as the area where multiple streams of traffic intersect with each other [52]. The time element begins when the first vehicle leaves the stop bar and ends when all vehicles have completely cleared the conflict area and begin accelerating, which is the most critical part of the process to ensure that discharge occurs efficiently.

The QCR is defined as shown in Equation (21):

$$QCR = \frac{N}{T} \quad (21)$$

where

- N represents the number of vehicles in the queue expressed in PCE units, and
- T denotes the time elapsed between the arrival of the front bumper of the first vehicle at the stop line and the exit of the rear bumper of the last vehicle from the conflict area.

3. Materials and Methods

The main objective of this study is to perform a systematic review of the scientific literature related to Passenger Car Equivalency (PCE) at urban signalized intersections. The review was conducted using the PRISMA 2020 guidelines [23] in order to provide consistency and an opportunity for the reproducibility of the review methods. The PRISMA methodology is widely recognized in the literature as a comprehensive framework for conducting systematic reviews, providing a structured and transparent approach to the review process. Additionally, a mixed-methods approach was employed. A qualitative thematic analysis was conducted by comparing the methodologies of the reviewed studies, and descriptive statistics were used to analyze publication trends and geographic distribution of research.

3.1. Protocol and Registration

The protocol for this systematic review was developed prior to the literature search and followed the PRISMA 2020 guidelines [23]. To support transparency and reproducibility, the review protocol was prospectively registered on the Open Science Framework (Registration: np3q9) [53]. The search strategy, eligibility criteria, and data extraction procedures were finalized prior to conducting the database searches on 24 November 2025. As an additional transparency measure, the completed PRISMA 2020 checklist is provided in the Supplementary Materials.

3.2. Research Design and Research Questions

This study was designed to address both the increasing number of publications on the topic and the technical complexity of PCE estimation methodologies. Consistent with the PRISMA 2020 guidelines, a research framework was developed to map the global research landscape as well as to synthesize reported PCE values for different vehicle types and methodologies used across different contexts. The review therefore addresses the following three research questions:

- RQ1: What methodological approaches have been used to estimate PCE values at signalized intersections, and how have these methods evolved over time?
- RQ2: What are the publication trends, geographic distribution, and collaboration patterns in PCE research at signalized intersections?
- RQ3: What PCE values have been reported for different vehicle types, and how do these vary across different traffic conditions and geographic contexts?

3.3. Eligibility Criteria

To ensure the selection of relevant studies, an inclusion/exclusion criteria list was developed. The scope of this review was defined as PCE at urban signalized intersections. Although the initial search terms were kept broad to capture all facility types, studies conducted at roundabouts, unsignalized junctions, freeways, weaving sections, or rural roads were excluded as they fall outside the defined scope. The primary focus was the estimation, evaluation, or analysis of Passenger Car Equivalency (PCE) within the scope of signalized traffic operation. Studies using other measures such as saturation flow or headways were included only where these were specifically used to derive or evaluate PCE values. The review considered PCE values reported under different geographic locations, traffic conditions, and vehicle classification schemes. The target outcomes were PCE values for various vehicle types and related traffic flow metrics used in their estimation.

For inclusion in this review, only peer-reviewed journal articles were considered, excluding conference papers, technical reports, dissertations, and book chapters. This decision was taken for the following reasons:

1. Journal articles provide more detail regarding the methodology used in the study and the specifics of the data collected and analyzed, whereas conference papers are constrained by page limits.
2. Peer-reviewed journal articles undergo a more rigorous evaluation process, thereby meeting the quality requirements for this systematic review.
3. All studies included in this review were required to pass a comprehensive quality assessment based on standardized bibliometric indicators such as journal h-index and citation counts. These metrics, essential for objective and reproducible quality evaluation, are not consistently available or comparable for conference proceedings.

For the subsequent qualitative synthesis, eligible studies were grouped according to the methodological approach employed (e.g., regression-based, headway-based, and simulation-based methods).

3.4. Information Sources and Search Strategy

The literature search was conducted across three major bibliographic databases that are considered to be comprehensive for transportation engineering research: Web of Science Core Collection (Clarivate Analytics), Scopus (Elsevier), and ScienceDirect (Elsevier). Although Scopus indexes ScienceDirect publications, a separate search was conducted directly in ScienceDirect to capture articles that may contain relevant terms in the full text rather than only in the title, abstract, or keywords. The databases were searched from their inception to the present date, with no retrospective time limits applied in order to include foundational works which may have influenced current methodologies.

The search strategy employed Boolean operators to combine terms related to PCE and traffic flow. The full search queries for each database are detailed in Appendix A. Although a consistent search structure was the aim, adaptations were necessary due to limitations in the interfaces. Specifically, ScienceDirect imposes a restriction of a maximum of eight Boolean connectors, so the search string for this database was simplified to capture the broadest set of relevant terms. All searches were completed and last updated on 24 November 2025.

To provide additional assurance of comprehensiveness, an additional literature review was completed checking the reference lists of all included studies (backward citation tracking) and conducting a forward citation search via Google Scholar to identify relevant publications.

3.5. Selection Process

To effectively manage the large number of search result records, they were classified using inclusion and exclusion criteria based on pre-defined keyword sets. Inclusion keywords referenced types of signalized traffic control facilities (e.g., 'pce', 'pcu', 'passenger car equivalent', 'traffic light', 'intersection', etc.), while exclusion keywords identified types of traffic control facilities to be excluded from the search (e.g., 'roundabout', 'motorway', 'freeway', etc.). After screening, duplicate records were identified and removed through DOI and title matching and all the data were then formatted into a single dataset. Subsequently, full-text assessment was performed by the authors on the list to determine whether or not they met the established inclusion/exclusion criteria. Studies relevant to the research question were identified for inclusion and subsequently subjected to quality assessment. Studies meeting the quality threshold formed the dataset for the methodological analysis and qualitative synthesis presented in this review.

3.6. Quality Assessment

The included studies underwent a systematic quality evaluation for their methodological robustness and reporting transparency. Established quality assessment tools were not adopted because these instruments are designed for clinical studies with criteria (e.g., randomization and blinding) that are not applicable to traffic engineering field research. The scoring criteria were therefore developed following the domain-specific approach recommended by Kitchenham and Charters [54] for engineering systematic reviews. Therefore, to perform this evaluation, we designed a 100-point grading rubric that comprised three main categories.

Publication Quality (30 points): This category evaluated both the journal's indexing status and its citation impact. Studies published in journals indexed in Web of Science or Scopus with established impact factors received higher scores (H-index component: 0–20 points), while citation rates relative to publication year were also considered (0–10 points). Journal h-index values were obtained from SCImago Journal & Country Rank SCImago [55]. H-index thresholds were calibrated to reflect the citation patterns typical of this field. The scoring scale was as follows: h-index ≥ 100 (20 points), 70–99 (17 points), 50–69 (14 points), 30–49 (11 points), 15–29 (8 points), and 5–14 (5 points). Journals not indexed in SCImago but indexed in Web of Science received 5 points, while journals not indexed in either database received 0 points. For discontinued journals where current indexing metrics were unavailable, only the citation count criterion was applied.

Methodological Quality (50 points): This category assessed five different criteria related to the methodological quality of the studies:

- (i) Clarity of the PCE method definition, which includes how explicitly the PCE method is defined, and the level of theoretical justification provided for the method definition (0–10 points);
- (ii) Data collection protocols, which include sample sizes, observation durations, and details regarding the types of equipment used during data collection (0–12 points);
- (iii) Site selection rationales and documentation of the intersection characteristics of the sites selected for the study (0–8 points);
- (iv) Criteria used to measure the number of vehicles per unit time (saturation flow) and the time interval between successive vehicles passing through an intersection (headway) (0–10 points);
- (v) Rigor of statistical analyses used in the study, including the use of validation procedures, goodness-of-fit measures, and significance testing (0–10 points).

Reporting Transparency (20 points): This category evaluated the extent to which the included studies reported PCE values by vehicle type (0–10 points), discussed the

limitations of the study (0–5 points), and allowed others to reproduce the methodologies presented in the studies (0–5 points).

Each of the studies was individually graded and categorized into one of four groups:

- High quality (80–100 points);
- Good quality (70–79 points);
- Acceptable quality (60–69 points);
- Excluded (<60 points).

Studies that scored less than 60 points were excluded from this review because of insufficient methodological quality or because they were published in predatory journals. Of the 49 studies that were assessed using the above methods, 40 met the quality threshold required for inclusion in this review. These 40 studies were further divided into the following three groups based on their quality scores (Figure 4):

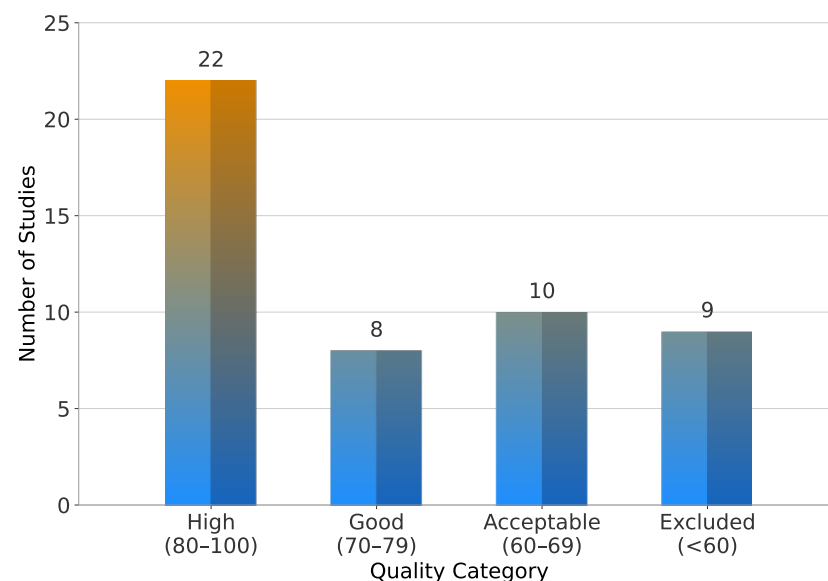


Figure 4. Distribution of studies by quality assessment category.

High quality ($n = 22$); good quality ($n = 8$); acceptable quality ($n = 10$). Nine studies were excluded from the analysis. The quality scores ranged from 20 to 100, and the median quality score for the studies included in our analyses was 79.

3.7. Data Extraction

A standardized data extraction form was developed in Microsoft Excel. The authors manually reviewed the full texts of the included studies to extract specific technical details such as study location, intersection geometry, signal timing parameters, traffic composition, and data collection techniques (e.g., field survey vs. simulation). The primary outcome extracted was PCE values for different vehicle types (e.g., automobiles, buses, and heavy vehicles). Secondary outcomes included saturation flow rates, headway values, and delay metrics where these were reported in relation to PCE estimation or validation. Additionally, specific PCE estimation methods employed in each study were recorded to enable methodological grouping for the qualitative synthesis. To ensure data accuracy, the extracted information was cross-verified by the authors.

3.8. Synthesis Methods

The synthesized dataset was investigated by means of a combination of qualitative and quantitative methods. Due to the large variability between studies in terms of geographic context, intersection characteristics, vehicle classification schemes, and PCE estimation

approaches, quantitative comparisons were limited to PCE values reported within the same estimation methods. A narrative synthesis approach was adopted to interpret and contextualize the findings across methodological groups.

In the qualitative synthesis, studies were systematically grouped according to the PCE estimation methodology employed (i.e., regression-based, headway-based, area/occupancy, delay based, and other analytical methods). The reported PCE values and vehicle classes were listed within each methodological group, along with the results of the studies. These were then compared on a descriptive basis, taking into account the contextual elements that could influence PCE estimation.

4. Results

A systematic search conducted across three academic databases yielded a total of 4368 records: Web of Science ($n = 1995$), ScienceDirect ($n = 1657$), and Scopus ($n = 716$). Study records were systematically filtered based on both title and abstract content. This filtering method utilized pre-defined combinations of keywords to locate studies that estimated either PCE (Passenger Car Equivalent) or PCU (Passenger Car Unit) at signalized intersections. Studies were excluded if their scope was on facility types that were not related to urban signalized intersections, such as highways, roundabouts, median block sections, and unsignalized intersections. As a result of the screening process, the number of potentially relevant articles was reduced to 234. After eliminating the duplicate study records ($n = 106$) through DOI and Title matching, 128 study records remained for a full-text evaluation.

During the full-text evaluation phase of the screening process, studies published in English peer-reviewed journals were evaluated. Studies published in conference proceedings and Procedia series publications were eliminated from further consideration. Additionally, studies utilizing previously established PCE values without proposing a new method for estimating PCE values and studies focused on subjects unrelated to PCE value estimation, including signal timing, accident analysis and/or driver behavior were also eliminated. Review articles were eliminated because they represented secondary research rather than primary research. Based on these criteria, 92 articles were excluded, leaving 33 studies from the database search.

As a result, a total of 49 articles met all the inclusion criteria: 33 from the database search and 16 from citation tracking. Following the quality evaluation, 9 studies were excluded due to insufficient methodological quality, resulting in 40 studies included in this review. The steps involved in the literature selection are shown in Figure 5.

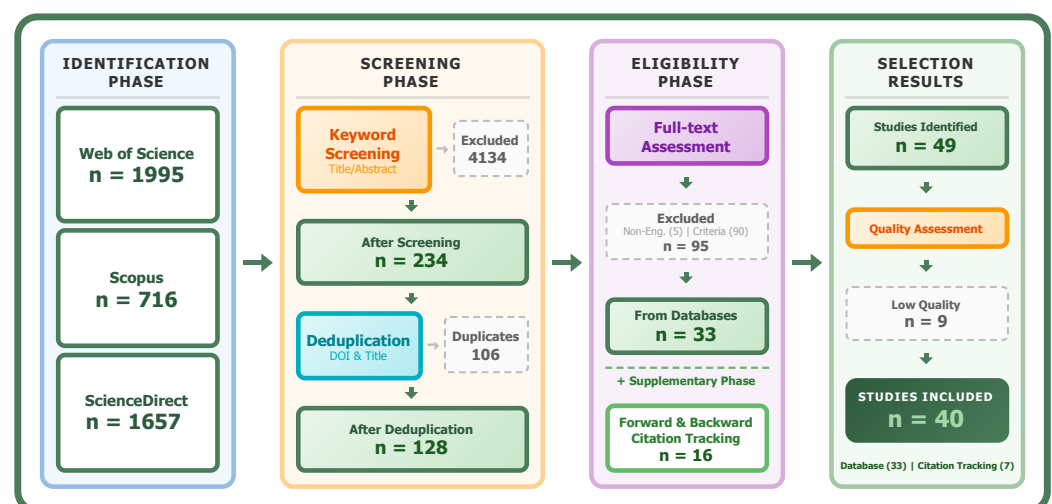


Figure 5. PRISMA 2020 flow diagram illustrating the systematic review and selection process.

4.1. Study Characteristics

The characteristics of the 40 included studies are presented in Tables 2 and 3. Regarding research design, field studies constituted the majority ($n = 27$, 67.5%), followed by simulation-based studies ($n = 6$, 15%) and combined field-simulation approaches ($n = 7$, 17.5%). Video recording was the most common data collection method, employed in over 70% of field studies. The PCE estimation methods employed in each study were also identified based on the methodological approach described in the original publications. Seven distinct method families were identified as follows: headway-based, regression-based, area occupancy, delay-based, capacity-based, queue-based, and optimization methods. Three studies employed multiple methods: Asaithambi et al. [1], Kimber et al. [7], Sun et al. [56], and were counted in each applicable category in the cross-tabulation analyses, resulting in 43 method applications from 40 included studies.

Table 2. Study characteristics of included studies ($n = 40$).

ID	Author(s)	Year	Country	Study Type	Method
1	Branston & van Zuylen [33]	1978	UK (London)	Field study	Regression
2	Keller & Saklas [39]	1984	USA	Simulation	Delay
3	Kimber et al. [7]	1985	UK	Field study	Headway, Regression *
4	Thamizh Arasan & Jagadeesh [57]	1995	India (Madras)	Field study	Regression
5	Kockelman & Shabih [58]	2000	USA (Austin, Texas)	Field study	Regression
6	Benekohal & Zhao [59]	2000	USA (Illinois)	Field + Simulation	Delay
7	Hossain [14]	2001	Bangladesh (Dhaka)	Field + Simulation	Regression
8	Rahman et al. [60]	2003	Japan (Yokohama)	Field study	Delay
9	Rahman et al. [61]	2004	Bangladesh (Dhaka)	Field study	Other
10	Rodriguez-Seda & Benekohal [62]	2006	USA (Chicago)	Field study	Delay
11	Hadiuzzaman et al. [37]	2008	Bangladesh (Dhaka)	Field study	Regression
12	Saha et al. [63]	2009	Bangladesh (Dhaka)	Field study	Headway
13	Hadiuzzaman & Rahman [64]	2010	Bangladesh	Field study	Regression
14	Washburn & Cruz-Casas [65]	2010	USA (Florida)	Field + Simulation	Headway
15	Radhakrishnan & Mathew [2]	2011	India (Mumbai)	Field study	Optimization
16	Mamun et al. [66]	2012	Bangladesh (Dhaka)	Field study	Headway
17	Sarraj [67]	2014	Palestine (Gaza)	Field study	Headway
18	Skabardonis et al. [68]	2014	USA (Oakland, Miami)	Field + Simulation	Other
19	Kollár [50]	2014	Hungary (Budapest)	Simulation	Capacity
20	Fornalchyk et al. [69]	2015	Ukraine	Simulation	Headway
21	Alex & Isaac [44]	2015	India (Trivandrum)	Simulation	Occupancy
22	Adams et al. [70]	2015	Ghana (Tamale)	Field study	Regression
23	Nassiri et al. [71]	2017	Iran (Tehran)	Field + Simulation	Delay
24	Mohan & Chandra [52]	2017	India (Simulated)	Simulation	Queue
25	Asaithambi et al. [1]	2017	India (Chennai)	Field + Simulation	Headway, Regression *
26	Barna et al. [51]	2018	Hungary	Simulation	Capacity
27	Zahiri & Chen [72]	2018	China (Hangzhou)	Field study	Headway
28	Mondal & Gupta [48]	2019	India (Allahabad)	Field study	Optimization
29	Aoyama et al. [73]	2020	Japan (Tokyo)	Field study	Headway
30	AlKheder [74]	2020	Kuwait	Field study	Headway
31	Li et al. [75]	2020	China (Nanjing)	Field study	Other
32	Patel & Dhamaniya [47]	2021	India (Multiple)	Field study	Occupancy
33	Suweda & Wedagama [76]	2021	Indonesia (Bali)	Field study	Regression
34	Sugiarto et al. [77]	2021	Indonesia (Banda Aceh)	Field study	Regression
35	Kariyana et al. [78]	2022	Indonesia (Bali)	Field study	Regression
36	Ghanim & Abu-Lebdeh [79]	2022	USA (Kentucky)	Field + Simulation	Headway
37	Sun et al. [56]	2022	China (Guiyang)	Field study	Headway, Occupancy *
38	Ahmed et al. [21]	2022	Pakistan (Karachi)	Field study	Regression
39	Jithender & Sushmitha [80]	2024	India (Warangal)	Field study	Queue
40	Maddu et al. [15]	2025	India (Multiple)	Field study	Occupancy

* Studies employed multiple methods.

Methods were identified as follows: (1) studies calculating PCE using time headway ratios between vehicle types were classified as headway-based methods; (2) regression-based methods were assigned when statistical regression models were employed to relate traffic flow parameters to vehicle composition; (3) area occupancy methods were classified when studies used spatial occupancy ratios rather than time-based measurements; (4) delay-based methods were identified when PCE derivation was based on vehicle delay comparisons; (5) capacity-based methods were assigned when studies derived PCE from capacity analysis; (6) queue-based methods were classified when queue discharge characteristics were the primary basis; and (7) optimization methods were identified when mathematical optimization techniques were used. As simulation-based studies generated synthetic data that were subsequently analyzed using one of the seven PCE estimation methods listed above, simulation was not classified as a separate methodology.

Table 3. Data collection methods, traffic conditions, and sample sizes (MC = Motorcycle).

ID	Author(s)	Data Collection	Traffic Condition	Sample Size
1	Branston & van Zuylen [33]	Manual counting	Homogeneous, lane-based	1 intersection, 130 obs
2	Keller & Saklas [39]	TRANSYT/7N simulation	Homogeneous, lane-based	4-node network, 8 links
3	Kimber et al. [7]	Event recorders	Homogeneous, lane-based	37 single lane streams
4	Thamizh Arasan & Jagadeesh [57]	Manual counting	Heterogeneous, non-lane-based	3 intersections
5	Kockelman & Shabih [58]	Video recording	Homogeneous, lane-based	2 intersections, 458 queues
6	Benekohal & Zhao [59]	Video + TRAF-NETSIM	Heterogeneous (2–30% trucks)	7 intersections
7	Hossain [14]	Video + MIXNETSIM	Heterogeneous, non-lane-based	Multiple intersections
8	Rahman et al. [60]	Video recording	Mixed (PC + HV), lane-based	7 intersections, 450 cycles
9	Rahman et al. [61]	Manual counting	Heterogeneous, non-lane-based	4 intersections
10	Rodriguez-Seda & Benekohal [62]	Video recording	Homogeneous, lane-based	34 cycles
11	Hadiuzzaman et al. [37]	Video recording	Heterogeneous, non-lane-based	5 intersections
12	Saha et al. [63]	Audio-based recording	Heterogeneous	10 intersections
13	Hadiuzzaman & Rahman [64]	Video recording	non-lane-based, heterogeneous	5 intersections
14	Washburn & Cruz-Casas [65]	Video + simulation	Homogeneous	6 intersections, 403 cycles
15	Radhakrishnan & Mathew [2]	Video recording	Highly heterogeneous	6 intersections, 86 cycles
16	Mamun et al. [66]	Audio-based recording	Heterogeneous mixed	14 intersections
17	Sarraj [67]	Video recording	Heterogeneous	3 intersections
18	Skabardonis et al. [68]	Video + VISSIM	Homogeneous (port access)	2 intersections
19	Kollár [50]	VISSIM simulation	Homogeneous	144 simulations
20	Fornalchik et al. [69]	VISSIM simulation	Mixed	192 experiments
21	Alex & Isaac [44]	TRAFFICSIM simulation	Heterogeneous	N/A
22	Adams et al. [70]	Video recording	Mixed, MC-dominated	3 intersections
23	Nassiri et al. [71]	Video + TRAF-NETSIM	Heterogeneous mixed	5 intersections
24	Mohan & Chandra [52]	VISSIM simulation	Heterogeneous, non-lane-based	4 approaches
25	Asaithambi et al. [1]	Video+simulation	Highly heterogeneous	1 intersection, 25 cycles
26	Barna et al. [51]	VISSIM simulation	Homogeneous	Multiple runs
27	Zahiri & Chen [72]	Video recording	Homogeneous, Lane-based	3 intersections
28	Mondal & Gupta [48]	Video recording	Heterogeneous, non-lane-based	3 intersections, 207 cycles
29	Aoyama et al. [73]	Video recording	Homogeneous	10 intersections
30	AlKheder [74]	Video recording	Mixed traffic	3 intersections
31	Li et al. [75]	Video recording	Mixed (MC + e-bikes), lane-based	2 intersections
32	Patel & Dhamaniya [47]	Video recording	Heterogeneous, non-lane-based	11 intersections, 285 cycles
33	Suweda & Wedagama [76]	Video recording	Mixed, MC-dominated	3 intersections
34	Sugiarto et al. [77]	Video recording	Heterogeneous (74% MC)	3 intersections, 520 cycles
35	Kariyana et al. [78]	Video recording(ATCS)	Heterogeneous (82% MC)	4 intersections
36	Ghanim & Abu-Lebdeh [79]	Video + VISSIM	Homogeneous	1 intersection, 820 headways
37	Sun et al. [56]	UAV monitoring	Mixed, lane-based	2 intersections
38	Ahmed et al. [21]	UAV aerial video	Heterogeneous	1200 video frames
39	Jithender & Sushmitha [80]	Video recording	Heterogeneous mixed	2 intersections, 365 cycles
40	Maddu et al. [15]	Video recording	Heterogeneous mixed	5 intersections

With 40 studies covering almost 50 years (1978–2025) across geographically diverse locations, the distribution of research across regions, time frames, and methodologies

should be examined to determine whether observed patterns represent systematic trends or random variability. Statistical analysis provides an opportunity to separate real trends from anecdotal observations, thereby strengthening the conclusions of this review and enabling more informed recommendations for future research directions. In the following subsections, detailed statistical analyses of the temporal distribution, geographic distribution, and methodological characteristics of the included studies are presented.

4.1.1. Temporal Distribution and Trend Analysis

A temporal trend analysis was conducted to measure the trends in publication frequency over time. However, due to the majority of years having either no or only one study, the data were aggregated into five-year blocks to remove the “noise” and determine the overall trend (Figure 6). A simple Ordinary Least Squares (OLS) linear regression model was used to evaluate the five-year average publication frequency as a function of the mid-point year for each block of years. The regression analysis revealed a statistically significant positive trend ($\beta = 0.21$ publications/year, $R^2 = 0.83$, $p < 0.001$). This finding was further validated using the Mann–Kendall non-parametric trend test ($Z = 3.67$, $p < 0.001$). These results confirm that research interest in PCE estimation at signalized intersections has grown substantially, with 65% of all included studies ($n = 26$) published from 2011 onwards.

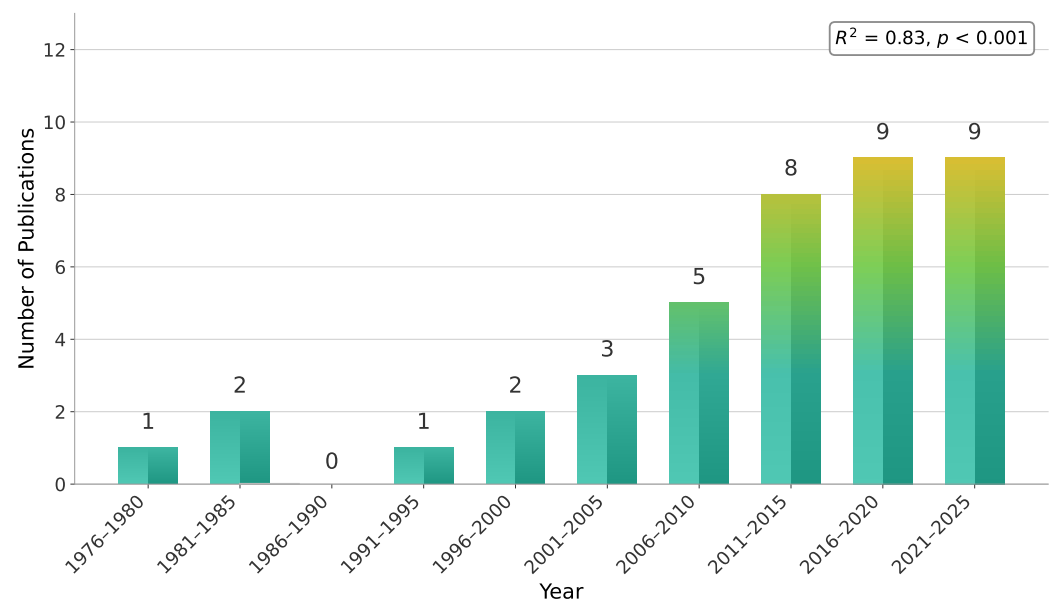


Figure 6. Temporal distribution of included studies by five-year publication period ($n = 40$).

4.1.2. Geographic and Methodological Characteristics

The distribution of the included studies across the world’s geographical regions and the methods used to estimate Passenger Car Equivalent (PCE) values were evaluated as part of the present review by applying Chi-square analysis. Table 4 presents seven Chi-square analyses examining patterns in the PCE literature. These are tests for geographic distribution of studies, preference for dynamic versus static PCE approaches, temporal trends in this preference, the relationship between method choice and study quality, representation of the seven estimation methods, and associations between method choice and both geographic region and publication period.

Table 4. Summary of Chi-square analyses for publication characteristics.

Analysis	χ^2	df	p-Value
Geographic distribution	26.60	3	<0.001 *
PCE type (Dynamic vs. Static)	8.10	1	0.004 *
PCE type $\times$ Time period	3.01	3	0.390
Quality $\times$ Method type	0.02	2	0.992
PCE method frequencies	21.20	7	0.003 *
Method $\times$ Geographic region	5.23	6	0.515
Method $\times$ Time period	8.86	6	0.182

* Statistically significant at $\alpha = 0.05$.

The geographic distribution is visualized in Figure 7, showing that studies are highly skewed across world regions ($\chi^2 = 26.60$, $df = 3$, $p < 0.001$), and studies from Asia ($n = 24$) dominate the literature with 60%. India ($n = 9$) and Bangladesh ($n = 6$) have been studied more than any other country within Asia. In contrast, studies from North America ($n = 7$) account for approximately 18%, whereas those from Europe ($n = 5$) and the Middle East/Africa ($n = 4$) account for approximately 12% and 10%, respectively.

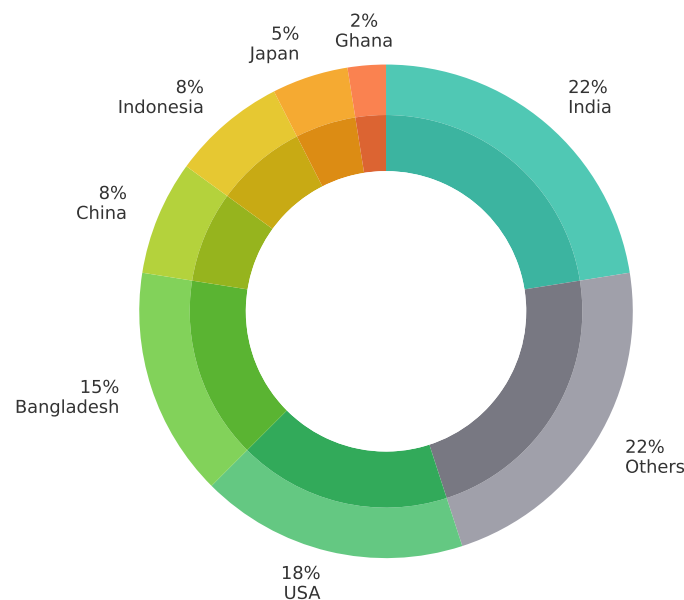


Figure 7. Geographic distribution of included studies ($n = 40$). Major contributors are India ($n = 9$), USA ($n = 7$), and Bangladesh ($n = 6$). Others include China, Indonesia ($n = 3$ each), Japan, UK, Hungary ($n = 2$ each), Iran, Palestine, Ukraine, Ghana, Kuwait, and Pakistan ($n = 1$ each).

The analysis also revealed a strong preference for dynamic methods in PCE estimation. Overall, 72.5% of studies employed a dynamic method for PCE estimation, whereas only 27.5% employed a static method, a difference that was statistically significant ($\chi^2 = 8.10$, $df = 1$, $p = 0.004$). The proportion of studies employing dynamic methods increased over time, from 50% for studies published prior to 2000 to 83% for studies published between 2016 and 2025. Although this temporal pattern appears to indicate that researchers increasingly recognize the importance of dynamic PCE values, it did not reach statistical significance ($\chi^2 = 3.01$, $df = 3$, $p = 0.390$) primarily because of the limited number of studies in the present review. It was found that no significant relationship exists between the methodological approach employed and the quality of the study ($\chi^2 = 0.02$, $df = 2$, $p = 0.992$), which indicates that the choice of PCE estimation method does not appear to affect overall research quality (Table 4).

A Chi-square goodness-of-fit test confirmed that PCE estimation methods were not equally distributed ($\chi^2 = 21.20$, $df = 7$, $p = 0.003$), with headway-based ($n = 12$) and

regression-based ($n = 13$) methods being predominant. No significant association was found between method category and geographic region ($\chi^2 = 5.23$, $df = 6$, $p = 0.515$; Table 5) or between method category and publication period ($\chi^2 = 8.86$, $df = 6$, $p = 0.182$; Table 6) (Since three studies employed multiple methods, Tables 5 and 6 include 43 method applications across 40 studies).

Table 5. Distribution of PCE estimation methods by geographic region.

Method	Developed	South Asia	Other	Total
Headway	4	3	5	12
Regression	3	6	4	13
Occupancy	0	3	1	4
Others	6	5	3	14
Total	13	17	13	43

Table 6. Distribution of PCE estimation methods by publication period.

Method	Early (<2010)	Middle (2010–2019)	Recent (2020+)	Total
Headway	2	6	4	12
Regression	6	3	4	13
Occupancy	0	1	3	4
Others	5	7	2	14
Total	13	17	13	43

Although these associations were not statistically significant, several qualitative patterns can be observed. The occupancy method was not applied in any study from developed countries, while 75% of occupancy-based studies originated from South Asia (Table 5), suggesting that area occupancy approaches may be emerging as a region-specific methodological preference. This pattern likely reflects the limitations of headway-based methods in heterogeneous, non-lane-based traffic conditions common in South Asian countries, where vehicles do not follow strict lane discipline and conventional time headway measurements become less meaningful. Additionally, the use of occupancy methods also showed a clear increasing trend over time, from 0 studies before 2010 to 3 studies in 2020+ (Table 6).

Overall, these data indicate that the PCE research at signalized intersections has developed into a well-established area of research with considerable methodological variety; however, the geographic distribution of this research remains unbalanced. The high number of studies from Asia indicates an actual need for this type of research in areas where there is mixed traffic, while it also points out the lack of similar research in Europe and Africa. The growing preference for dynamic PCE estimation over static values reflects a shift toward treating traffic parameters as active variables and context-sensitive traffic analysis, which may eventually influence updates to national capacity manuals.

4.2. Methodological Approaches

Table 7 presents advantages and the disadvantages of the methods considered in each study and Table 8 the distribution of PCE estimation methods across 40 studies examining PCE estimation at signalized intersections. The analysis reveals eight distinct methodological categories, with the regression method (13 studies) and headway method (12 studies) being the most frequently employed approaches, collectively accounting for approximately 58% of the reviewed literature.

Regarding traffic characteristics presented in Table 8, traffic composition was the most commonly considered factor (30 studies, 75%), followed by saturation flow (19 studies, 48%), predominantly in occupancy, delay-based, and regression methods. The leader–follower

relationship, which captures the interactions between consecutive vehicles (7 studies, 18%) and queue position effects (6 studies, 15%) were examined less frequently, suggesting an area requiring further research attention.

Table 7. Advantages and disadvantages of various methods used in PCE estimation at signalized intersections.

Method	Advantages	Disadvantages
Headway Ratio	- Simple and straightforward formulation ($PCE = h_i/h_c$), easy to understand and apply [27] - Direct relationship with saturation flow through $S = 3600/h$ [73] - Low-cost field application requiring only video camera or audio recorder [63,72] - Can be corrected with Scraggs factor when independence assumption fails [7]	- Violation of independence assumption; headway depends on both subject and preceding vehicle type [7,81] - Only valid when queue extends beyond green phase [82] - Treats PCE as constant, but it varies with volume, composition, and geometry [1] - Needs sufficient observations for all vehicle-pair combinations [66]
Regression	- Does not require individual headway measurement; works on count basis [37,38] - Simultaneously estimates PCE and saturation flow [33] - Suitable for non-lane-based heterogeneous traffic [14,37] - Dynamic PCE models dependent on vehicle composition can be developed [38]	- Negative PCE values may occur, difficult to interpret and apply in practice [37] - Results are location-specific, requiring separate calibration for each intersection [14,36] - Saturation condition determination is subjective [36]
Area Occupancy	- Explicitly accounts for two-dimensional nature of traffic flow [44,45] - Captures filtering and seepage behavior of smaller vehicles [46,47] - Applicable to non-lane-based heterogeneous traffic [45]	- Accuracy depends on reliable speed and area measurements [43,45] - Assumes steady-state traffic conditions [2] - Projected rectangular area oversimplifies actual vehicle footprint [47]
Delay-Based	- Accounts for delay caused by heavy vehicles across the entire queue [39,61] - Delay is directly related to capacity and level of service [59] - Can be disaggregated by queue position, signal timing, and vehicle type [61] - Suitable for volume-based prediction models [71]	- Calibration is mandatory if simulation is used [71] - Produces unreliable results under LOS F conditions [59] - Measuring delay is more complex and costly than measuring headway [39] - Higher computational complexity [39]
Queue-Based	- Does not require car-following assumption, applicable to heterogeneous traffic [52,83] - Eliminates the need for saturation flow measurement [80] - Captures actual discharge behavior of different vehicle types [80] - Requires only macroscopic-level data collection	- Valid only under saturated queue conditions [52,83] - Queue clearance rate is sensitive to vehicle position [52] - Does not account for interaction effects between vehicle types [80]
Capacity-Based	- Simple data extraction; only total vehicle counts required [50,51] - Captures all delay components holistically [50] - Consistent comparison across different intersection types [50,51]	- Simulation-only application; cannot be used with field data [50,51] - Homogeneous flow assumption may not reflect real mixed traffic [50] - At low volumes, PCE approaches 1.0 regardless of vehicle type [50,51]
Optimization-Based	- Produces context-specific PCE values reflecting actual traffic conditions [2,48] - Handles non-lane-based mixed traffic [2] - Theil's coefficient provides normalized, objective measure of model fit [2] - Simultaneously estimates PCE and saturation flow [48]	- Requires substantial field data collection with video recording [2,48] - Results are location-specific, limiting transferability [2] - Identification of saturated green region involves subjective decisions [2]

Table 8. Summary of methods: PCE dependency factors, measured geometric factors, and PCE type preferences in PCE estimation at signalized intersections.

Method	Study	PCE Type			Traffic Characteristics			Geometric		
		Static	Dyn.	S.F.	Comp.	L-F	QP	Dir.	AW	G
Headway	Kimber et al. (1985) [7] *	✓	–	✓	–	–	–	T	–	–
	Saha et al. (2009) [63]	✓	–	–	✓	✓	–	T	✓	–
	Washburn and Cruz-Casas (2010) [65]	✓	–	–	–	✓	–	T	✓	–
	Mamun et al. (2012) [66]	✓	–	–	–	✓	–	R	–	–
	Sarraj and Yahya (2014) [67]	✓	–	–	–	–	–	T	–	–
	Fornalchyk et al. (2015) [69]	–	✓	–	–	–	✓	T + R	✓	–
	Asaithambi et al. (2017) [1] *	✓	–	–	–	✓	–	T	✓	–
	Zahiri and Chen (2018) [72]	–	✓	–	✓	–	–	T	–	–
	Aoyama et al. (2020) [73]	–	✓	–	✓	✓	–	T	–	–
	AlKheder (2020) [74]	✓	–	–	–	–	–	T	✓	–
	Ghanim and Abu-Lebdeh (2022) [79]	–	✓	✓	✓	–	–	T	–	–
	Sun et al. (2022) [56] *	–	✓	–	–	–	–	L + T	✓	–
Regression	Branston and van Zuylen (1978) [33]	✓	–	–	✓	–	–	L + T	✓	–
	Kimber et al. (1985) [7] *	✓	–	✓	–	–	–	T + R	–	–
	Thamizh Arasan and Jagadeesh (1995) [57]	–	✓	✓	✓	–	–	T	✓	–
	Kockelman and Shabih (2000) [58]	✓	–	–	✓	–	–	L + T + R	–	–
	Hossain (2001) [14]	–	✓	✓	✓	–	–	L + T + R	✓	–
	Hadiuzzaman et al. (2008) [37]	–	✓	–	✓	–	–	L + T + R	✓	–
	Hadiuzzaman and Rahman (2010) [64]	–	✓	–	✓	–	–	L + T + R	✓	–
	Adams et al. (2015) [70]	✓	–	–	✓	–	–	T	✓	–
	Asaithambi et al. (2017) [1] *	–	✓	✓	✓	–	–	T	✓	–
	Sugiarto et al. (2021) [77]	✓	–	–	✓	–	–	L + T + R	✓	–
	Suweda and Wedagama (2021) [76]	–	✓	✓	✓	–	–	T	✓	–
	Kariyana et al. (2022) [78]	–	✓	✓	✓	–	–	T	✓	–
	Ahmed et al. (2022) [21]	✓	–	–	✓	–	–	T	✓	–
Occupancy	Alex and Isaac (2015) [44]	–	✓	✓	✓	–	–	T	✓	–
	Patel and Dhamaniya (2021) [47]	–	✓	✓	✓	–	–	L + T + R	✓	–
	Sun et al. (2022) [56] *	–	✓	✓	✓	–	–	L + T	✓	–
	Maddu et al. (2025) [15]	–	✓	✓	✓	–	–	T	✓	–
Delay-Based	Keller and Saklas (1984) [39]	–	✓	✓	✓	–	–	T	–	–
	Benekohal and Zhao (2000) [59]	–	✓	–	✓	–	–	T	✓	–
	Rahman et al. (2003) [60]	–	✓	–	✓	–	✓	T	–	–
	Rodriguez-Seda and Benekohal (2006) [62]	–	✓	–	–	–	✓	T	–	–
	Nassiri et al. (2017) [71]	–	✓	✓	✓	–	–	L + T + R	✓	–
Capacity-Based	Kollár (2014) [50]	–	✓	–	–	–	–	L + T + R	✓	–
	Barna et al. (2018) [51]	–	✓	✓	–	–	–	L + T + R	✓	–
Queue-Based	Mohan and Chandra (2017) [52]	–	✓	✓	✓	–	–	T	✓	–
	Jithender and Sushmitha (2024) [80]	–	✓	–	✓	–	–	L + T + R	✓	–
Optimization	Radhakrishnan and Mathew (2011) [2]	–	✓	✓	✓	–	–	L + T + R	✓	–
	Mondal and Gupta (2019) [48]	–	✓	–	✓	–	✓	L + T + R	✓	–
Other	Rahman et al. (2004) [61]	–	✓	–	✓	–	–	L + T + R	✓	–
	Skabardonis et al. (2014) [68]	–	✓	–	✓	–	✓	T	–	–
	Li et al. (2020) [75]	–	✓	–	–	–	–	L + T + R	✓	–

* Authors conducted multiple methods in their studies. Note: ✓ denotes the factor considered in the study.

Abbreviations: S.F. = Saturation Flow; Comp. = Traffic Composition; L-F = Leader-Follower Relationship; QP = Queue Position; Dir. = Direction (L: Left, T: Through, R: Right); AW = Approach Width; G = Grade; Dyn. = Dynamic.

Movement direction analysis varies considerably across studies. Through movements (T) were examined in all studies, while comprehensive analyses covering all three movement directions (L + T + R) were conducted in 15 studies (38%). This distribution indicates a research emphasis on through movements.

From a geometric perspective, approach width was considered in 28 studies (70%), establishing it as the most frequently examined geometric parameter. Notably, none of the reviewed studies incorporated gradient effects in their PCE estimation, representing a significant gap in the literature, particularly for intersections located in hilly terrain where grade can substantially influence vehicle performance and headway characteristics.

4.3. Cross-Study PCE Value Comparisons

Comparing findings across multiple studies using the same methodology enables validation of reported patterns and strengthens the generalizability of conclusions. Furthermore, this approach can reveal consistencies across studies that may not be apparent when each study is examined in isolation. In this section, cross-study comparisons are presented for methodologies with sufficient number of studies; single-study methodologies are excluded from this analysis as cross-study validation is not possible.

4.3.1. Headway Method

The headway-based method is one of the most common methods of estimating PCEs at signalized intersections for both homogeneous and heterogeneous traffic. Table 9 presents a controlled comparison of PCE values derived from headway-based methods across twelve studies from diverse geographic contexts.

Table 9. Cross-study comparison of PCE values using headway method.

Regime	Study (City, Country)	2W	3W	Car	LCV	Bus	Truck	Key Finding
NLB	Sarraj and Yahya (2014) [67] (Gaza, Palestine)	–	1.51	1.00	1.43	–	2.23	Animal-driven cart values differ from India
NLB	Asaithambi et al. (2017) [1] (Chennai, India)	0.40	0.73	1.00	1.30	–	2.06	PCE values differ from IRC values
NLB	Saha et al. (2009) [63] (Dhaka, Bangladesh)	–	0.86	1.00	1.42	2.16	–	Modern buses yield lower PCE (2.16 vs. 3.00)
NLB	Mamun et al. (2012) [66] (Dhaka, Bangladesh)	0.69	0.94	1.04	1.54	2.37	–	PCE values for right-turning vehicles
LB	Kimber et al. (1985) [7] (UK – National)	–	–	1.00	1.53	1.87	2.29	Headway ratio aligns with signal settings
LB	Washburn and Cruz-Casas (2010) [65] (Florida, USA)	–	–	1.00	1.80–2.20	–	2.80	Impact sensitive to vehicle size and queue position
LB	Fornalchyk et al. (2015) [69] (Lviv, Ukraine)	–	–	1.00	–	1.35–4.14	1.35–4.14	Dynamic PCE model reduces delays by 7.6%
LB	Zahiri and Chen (2018) [72] (Hangzhou, China)	–	–	1.00	1.26–1.31	–	–	SUVs PCE rises from 1.26 to 1.31 on rainy days
LB	AlKheder (2020) [74] (Kuwait City, Kuwait)	–	–	1.00	1.11–1.26	1.48	1.68	Low values indicate car-like driving agility
LB	Aoyama et al. (2020) [73] (Tokyo, Japan)	–	–	–	–	–	1.31–1.59	PCE relates to traffic function and HV proportion
LB	Ghanim and Abu-Lebdeh (2022) [79] (Kentucky, USA)	–	–	1.00	–	–	2.10–2.35	PCE ranges based on truck percentage
LB	Sun et al. (2022) [56] (Guiyang, China)	–	–	1.00	–	1.42–2.84	–	PCE varies by intersection and period

Abbreviations: NLB: Non-Lane-Based; LB: Lane-Based; 2W: Two-Wheeler; 3W: Three-Wheeler; LCV: Light Commercial Vehicle.

Non-Lane-Based Traffic Findings

In heterogeneous traffic conditions, two-wheeler PCE values show notable variation between studies. Asaithambi et al. [1] reported 0.40 for Indian conditions in Mangalore, while Mamun et al. [66] found 0.69 in Dhaka, Bangladesh. This significant difference can be attributed to the fact that Mamun's values were for right-turn movements only, which required longer path lengths and slower speeds.

Three-wheeler PCE values exhibit substantial variation across studies, ranging from 0.73 (Asaithambi et al. [1]) to 1.51 (Sarraj and Yahya [67]), with intermediate values of 0.86 (Saha et al. [63]) and 0.94 (Mamun et al. [66]). The differences among the studies may be a result of varying contextual elements. Sarraj & Yahya's [67] notably high value reflects the use of animal-driven carts rather than motorized vehicles, whereas Mamun et al. [66] found a higher value (0.94) consistent with their right-turn-specific measurement approach noted above. Saha et al. [63] measured an intermediate value of 0.86 partially due to poor road surface condition. The difference between Asaithambi et al. [1] (0.73) and Saha et al. [63] (0.86) can be further explained by traffic composition effects. Two-wheeler vehicles were predominant (71%) at the site of Asaithambi's [1] study; thus, the majority of interactions were made with motorcycle traffic instead of automobile traffic. In contrast, Saha's [63] study sites contained significantly more automobile traffic (as high as 78%). When passenger cars dominate the traffic stream, a rickshaw creates greater relative impedance compared to cars, resulting in a higher PCE value.

Heavy vehicle PCE values in non-lane-based traffic show relatively consistent results, ranging from 2.06 to 2.37 across South Asian studies.

Lane-Based Traffic Findings

Heavy vehicle PCE values indicate a greater range of values (1.31–2.8) compared to the results of non-lane-based studies. The primary reasons for these differences include vehicle sub-categorization, operational variables, environmental factors, and technological changes. While many studies treat all heavy vehicles as a single category, Washburn and Cruz-Casas [65] differentiated by physical size, reporting distinct values of 1.80 for small trucks, 2.2 for medium trucks, and 2.8 for large trucks. Fornalchyk et al. [69] estimated a PCE value of 1.35 for heavy vehicles with high acceleration capabilities, while vehicles with poor technical condition and slow acceleration can reach values as high as 4.14.

Regional specifications also emerge in lane-based studies. AlKheder [74] reported relatively low PCE values for pick-ups (1.11) and SUVs (1.14) in Kuwait, which indicated that both types of vehicles are operated similarly to passenger cars in terms of driving aggressiveness. Zahiri and Chen [72] found that the SUVs PCE increased from 1.26 to 1.31 on rainy days, as the decreased visibility resulted in the following vehicle maintaining larger safety gaps.

Additionally, Sun et al. [56] found that even in relatively homogeneous Chinese traffic (94% cars with good lane discipline), the headway-based method yielded lower bus PCE values (1.52–2.27) compared to travel-time (2.55–3.15) and speed-based methods (2.82–3.89). This suggests that single-parameter methods like headway ratio may underestimate vehicle impedance regardless of traffic composition, as they do not account for vehicle dimensions.

4.3.2. Regression Method

The regression-based method estimates PCE values by regressing saturated green time and the number of vehicles by type leaving during a given time period. In this context, the ratio of each regression coefficient by vehicle type to the regression coefficient for a passenger car yields the PCE value. There are two counting methods used to determine the

number of vehicles: synchronous (i.e., vehicles are counted when exactly at saturation) and asynchronous (vehicles are counted throughout all green phase times).

Table 10 presents PCE values derived from regression-based methods across non-lane-based and lane-based studies.

Table 10. Cross-study comparison of PCE values using regression method.

Regime	Study (City, Country)	2W	3W	Car	LCV	Bus	Truck	Key Finding
NLB	Thamizh Arasan and Jagadeesh (1995) [57] (Madras, India)	0.22–0.38	0.58–0.64	1.00	–	2.11–2.83	2.11–2.83	Saturation flow higher in mixed traffic
NLB	Hossain (2001) [14] (Dhaka) [Async]	0.23–0.54	0.51–1.40	0.69–1.13	0.82–1.27	1.32–1.56	1.13–1.40	Saturation flow modeled as aggregate
NLB	Hadiuzzaman et al. (2008) [37] (Dhaka) [Sync]	−1.06–0.90	0.22–0.92	1.00	1.21–2.68	2.27–4.56	–	PCE changes with composition
NLB	Hadiuzzaman and Rahman (2010) [64] [Sync]	0.29	0.52	1.00	1.82	2.68	–	MC can yield negative PCE values
NLB	Adams et al. (2015) [70] (Tamale, Ghana) [Sync]	0.30–0.56	0.67–0.75	1.00	–	1.52–1.68	1.52–1.68	High MC needs queue storage areas
NLB	Suweda and Wedagama (2021) [76] (Bali) [Sync]	0.15–1.02	–	1.00	–	–	0.23–0.87	Truck PCE low due to tiny %
NLB	Sugiarto et al. (2021) [77] (Banda Aceh) [Sync]	0.24	0.80	1.00	–	–	–	Bayesian approach provides robustness
NLB	Kariyana et al. (2022) [78] (Denpasar) [Sync]	0.02–0.80	–	1.00	–	–	0.10–0.90	Extreme MC behavioral variance
NLB	Ahmed et al. (2022) [21] (Karachi) [Sync]	0.20	0.50	1.00	1.20–2.80	3.10	3.00	Area occupancy-based framework
LB	Branston and van Zuylen (1978) [33] (London) [Async]	0.04	–	1.00	1.14	1.79	1.74	Sync method needs bias correction
LB	Branston and van Zuylen (1978) [33] (London) [Sync]	−0.08	–	1.00	1.28	1.61	1.59	Async provides direct results
LB	Kimber et al. (1985) [7] (UK) [Sync]	–	–	1.00	1.50	2.03	2.38	Sync aligns with headway ratio
LB	Kimber et al. (1985) [7] (UK) [Async]	–	–	1.00	1.22–1.24	1.31–1.63	1.73–1.80	Async 25% lower than headway
LB	Kockelman and Shabih (2000) [58] (Austin) [Sync]	–	–	1.00	1.07–1.41	–	–	LDTs as cars underestimates congestion

Abbreviations: NLB: Non-Lane-Based; LB: Lane-Based; Sync: Synchronous; Async: Asynchronous; 2W: Two-Wheeler; 3W: Three-Wheeler; LCV: Light Commercial Vehicle; MC: Motorcycle.

Non-Lane-Based Findings

Motorcycle PCE values exhibit the widest variation among all vehicle categories, ranging from negative values to above unity. Hadiuzzaman et al. [37] stated that their values ranged from −1.056 to 0.90 across approaches in Dhaka, whereas Hadiuzzaman and Rahman [64] reported a consolidated average of 0.29 using the same dataset. The seemingly contradictory results are a direct result of the methodologies used by each study; in particular, the 2008 study contained approach-specific values, which included both positive and negative coefficients, and the 2010 study did not include negative outliers in their average calculations. The negative PCE values occur because motorcycles penetrate queues through inter-vehicular gaps, position themselves at the front, and discharge faster than cars when the signal turns green, effectively increasing capacity beyond nominal levels.

Thamizh Arasan and Jagadeesh [57] reported more consistent values of 0.30–0.38 in Madras, similar to those reported by Adams et al. [70], who reported values ranging from 0.30 to 0.56 in Tamale, Ghana, where the proportion of motorcyclists accounted for between 43 and 70 percent of all traffic.

Indonesian studies demonstrate extreme variability in motorcycle PCE values. Suweda and Wedagama [76] reported values ranging from 0.15 to 1.02 across three Bali intersections, concluding that increased motorcycle proportions did not result in decreased discharge

headways; instead, rider behavior and the lack of lane discipline led to random positioning, producing PCE values unrelated to composition. Kariyana et al. [78], who also studied Denpasar, Indonesia, reported an even wider range of motorcycle PCEs (0.02 to 0.8), reflecting substantial behavioral differences among motorcyclists at that location.

However, Sugiarto et al. [77] found a relatively constant motorcycle PCE value of 0.24 at Banda Aceh, Indonesia using a Bayesian linear regression model based upon 520 signal cycle observations, suggesting that probabilistic approaches may provide more robust estimates in high-variance traffic conditions. Ahmed et al. [21] reported a motorcycle PCE of 0.2 in Karachi, Pakistan, consistent with Indonesian Bayesian estimates.

Three-wheeler PCE values show moderate variation reflecting vehicle motorization differences. Hossain [14] found rickshaw values of 0.51–0.647 in Dhaka for non-motorized cycle rickshaws, while Hadiuzzaman et al. [37] reported a wider range of 0.215–0.922 for motorized autorickshaws with superior acceleration capabilities. Other studies reported similar ranges: Hadiuzzaman and Rahman [64] found a value of 0.52, Thamizh Arasan and Jagadeesh [57] reported 0.58–0.64 for autorickshaws in India, and Sugiarto et al. [77] estimated 0.80 in Banda Aceh, representing a 60 percent deviation from the 0.50 value specified by the Indonesian Highway Capacity Manual (IHCM) [11]. This deviation likely reflects the larger physical dimensions of modern motorized rickshaws compared to the older vehicles in use when the IHCM [11] was first published in 1997.

Adams et al. [70] reported that tricycle values ranged between 0.67 and 0.75 in Ghana. However, the tricycle coefficient was only statistically significant at a 90 percent confidence interval because there were few samples to assess. Ahmed et al. [21] established that the PCE value of motorized rickshaws in Pakistan is 0.5 using area occupancy-based regression.

Heavy vehicle PCE values vary significantly between studies as a result of differing methodologies and context; Hadiuzzaman et al. [37], using a synchronous methodology, found bus values of 2.273–4.564. These are much higher than the asynchronous simulation-based study of Hossain [14], which identified bus values of 1.315–1.555 and truck values of 1.132–1.404. This is consistent with lane-based studies that have shown a systemic underestimation by asynchronous methods due to variability introduced by the inclusion of non-saturated periods.

In contrast, Thamizh Arasan and Jagadeesh [57] identified bus/truck values of 2.11–2.83 in India, whilst Hadiuzzaman and Rahman [64] identified a bus PCE value of 2.68 and minibus PCE value of 1.82, and Adams et al. [70] identified lower bus/truck values of 1.52–1.68 in Ghana due to the smaller vehicle sizes present in West African fleets. The highest values were reported by Ahmed et al. [21] in Karachi, with a bus PCE of 3.1 and a truck PCE of 3.0, which accounts for the larger physical footprint of heavy vehicles. Anomalously low values were identified within Indonesian studies: Suweda and Wedagama [76] reported 0.23–0.87, and Kariyana et al. [78] reported 0.1–0.9. These values were attributed to the minimal number of trucks present in traffic compositions.

Lane-Based Findings

Heavy vehicle PCE values show notable variation both between methods and across studies. Kimber et al. [7] reported heavy goods vehicle values of 2.38 (synchronous) versus 1.73 (asynchronous), demonstrating that asynchronous regression systematically underestimates PCE values by approximately 25% due to variability in car-to-car headways. Branston and van Zuylen [33] found lower lorry values of 1.74 (asynchronous) and 1.59 (synchronous) at their single suburban London site. The difference between Kimber's 2.38 and Branston's 1.74 can be attributed to Kimber's larger dataset across 35 sites, which captured greater variability in heavy vehicle characteristics and driving conditions.

Bus/coach PCE values also vary across UK studies. Kimber et al. [7] reported 2.03 (synchronous) and 1.80 (asynchronous), while Branston and van Zuylen [33] found lower values of 1.79 (asynchronous) and 1.61 (synchronous). Branston's lower values reflect site-specific conditions including a dedicated slip lane that reduced vehicle interactions.

Van PCE values demonstrate relative consistency despite geographic differences between studies. With synchronous counting, Branston and van Zuylen [33] reported 1.28 in London, whereas Kockelman and Shabih [58] found 1.34 in Austin, Texas. Kockelman and Shabih [58] further demonstrated the importance of vehicle sub-categorization: large SUVs (1.41) exhibited 32% higher PCE values than small SUVs (1.07), highlighting that treating all light-duty trucks as equivalent to passenger cars significantly underestimates urban congestion.

4.3.3. Delay-Based Method

The delay-based method estimates PCE values by comparing the delay caused by different vehicle types at signalized intersections. As presented in Table 11, all of the studies listed were lane-based and located within the United States, Japan, or Iran. According to Nassiri et al. [71], although Iranian drivers do not always follow strict lane discipline, this was addressed in their data normalization process using the roadway widths, and the results can thus be treated as lane-based for comparative purposes.

Table 11. Cross-study comparison of PCE values using delay-based method.

Study (City, Context)	Car	Bus	Truck/HGV	LCV	Key Finding
Keller and Saklas (1984) [39] (Simulation, USA)	1.00	1.14–1.22 (LOS-dep.)	1.24–1.54 (by type and LOS)	1.09–1.14	PCE values stable until forced flow (LOS F)
Benekohal and Zhao (2000) [59] (Illinois, USA, Sim.)	1.00	–	1.00–1.37 (SUT), 1.00–2.18 (CT)	–	D_PCE as function of volume and truck %
Rahman et al. (2003) [60] (Yokohama, Japan)	1.00	1.18–1.56 (prop.-dep.)	1.18–1.56 (prop.-dep.)	–	PCE varies with HV position in queue
Rodriguez-Seda and Benekohal (2006) [62] (Chicago, USA)	1.00	1.05–1.76; 5.1–5.9 (fail)	–	–	Stopping buses have different effect than trucks
Nassiri et al. (2017) [71] (Tehran, Iran, Sim.)	1.00	–	1.07–3.60; 1.07–2.07 (gen.)	–	d-PCE sensitive to volume and movements

Bus PCE Values

Variation in bus PCE values was observed across the reviewed studies. Keller and Saklas [39] identified through-moving bus PCE Values ranging from 1.14 to 1.22 while Rahman et al. [60] reported large vehicle PCE values in Yokohama of 1.18–1.56. However, Rodriguez-Seda and Benekohal [62] separated stopping and non-stopping buses in Chicago: the PCE values generated by stopping buses were 1.05–1.76 under normal conditions; however, when the bus resulted in an intersection failure, the PCE values were significantly higher (5.1–5.9). This difference highlights that dwell time and signal timing interactions are critical factors not captured by studies treating buses as non-stopping heavy vehicles.

Truck/Heavy Vehicle PCE Values

Heavy vehicle PCE values demonstrate a consistent range with variations explained by traffic conditions and vehicle classification. Keller and Saklas [39] reported 1.24–1.54, with higher values at forced flow conditions. Benekohal and Zhao [59] differentiated between single-unit trucks (1.00–1.37) and combination trucks (1.00–2.18), with the higher upper bound for combination trucks reflecting their longer length and poorer acceleration. Rahman et al. [60] reported 1.18–1.56, with variation dependent on heavy vehicle proportion

and queue position. Nassiri et al. [71] found the widest range of 1.07–3.6 in Tehran, with highest values at approaches with three movements, attributed to combined effects of traffic volume and movement complexity.

4.3.4. Area Occupancy Method

Among the reviewed literature, several studies utilized time/occupancy-based methods for PCE estimation at signalized intersections [15,47,56]. In particular, Sun et al. [56] distinguished their approach by employing a length-based (occupancy) ratio adapted to lane discipline, whereas the other approaches focused on area. Additionally, a single research article applied a modified version of the “Area Occupancy” method [44]. Although distinct in terminology, these methods were evaluated under the same methodological framework because they share the same focus: quantifying the impedance caused by a vehicle based on the dynamic interaction of its physical dimensions (Area or Length) and clearance time ($\text{Space} \times \text{Time}$), similar to the time–occupancy approach.

A comprehensive comparison of these studies is presented in Table 12.

Table 12. Overview of area/occupancy-based PCE estimation methods.

Parameter	Patel and Dhamaniya (2021) [47]/ Maddu et al. (2025) [15]	Alex and Isaac (2015) [44]	Sun et al. (2022) [56]
Method	Time Occupancy Method	Modified Area Occupancy	Dual Approach: Travel-Time and Speed-Based
Math Basis	Occupancy (Time)	Space (Area) $\times$ Time	Linear Space (Length) $\times$ Time/Speed
Context	India (Heterogeneous, non-lane-based)	India (Simulation, non-lane-based)	China (Mixed, Lane-Based)
Dimension	Area (Due to lateral seepage)	Area (Simulated occupancy)	Length (Due to strict lane discipline)
Width Band	Variable (4.5 m–14.0 m)	Variable (3.5 m–10.5 m)	Variable (7.0 m–12.5 m)
Traffic Comp.	High-Density 2W (>40%)	Controlled (0–50%)	Low/Moderate 2W (~18%)

The area/occupancy-based methods are especially sensitive to traffic composition as they measure the physical use of the road width space rather than just the time gap between vehicles. Therefore, traffic composition and approach width data are available in all five studies. A controlled comparison is used to evaluate the interaction effect between approach width, traffic culture, and estimation method. As shown in Tables 13 and 14, approaches with similar geometries were paired to observe the divergence in PCE values driven by local traffic characteristics.

There are three general similarities found for two-wheelers in this comparative analysis of data. Firstly, under similar geometric (width ~9–10 m) and traffic compositions (2W% ~60–65%) Tier-1 cities from both Indian studies have provided generally consistent findings: Patel and Dhamaniya’s [47] Ahmedabad approaches (0.13–0.32) and Maddu’s [15] Pune approaches (0.20–0.26) have results within each other’s PCE range. This cross-study consistency validates the time occupancy methodology when traffic culture is comparable.

Secondly, when two-wheeler proportions exceed 70% and approach widths decrease to less than 7 m, there is a critical divergence in terms of PCE between Tier-1 and Tier-3 cities. High two-wheeler densities enable efficient seepage behavior, as observed in Patel and Dhamaniya’s [47] Ahmedabad data (Tier-1), where vehicles systematically fill gaps and generating lower PCE values (0.14–0.29). However, in Maddu et al.’s [15] Chandrapur data (Tier-3), similar geometric and compositional conditions yield a 55% higher maximum PCE (0.45 vs. 0.29). This divergence is attributed to erratic driving patterns in smaller cities that disrupt the seepage efficiency observed in metropolitan areas.

Table 13. Comprehensive controlled comparison of 2W PCE values.

Width	Study (City)	Approach	Method	% 2W	PCE	Key Finding
Narrow	Patel and Dhamaniya (2021) [47] (Ahmedabad)	A-03	Time Occ.	79.4%	0.14–0.29	High-density swarming allows tight packing
Narrow	Maddu et al. (2025) [15] (Chandrapur)	A-06	Time Occ.	74.2%	0.23–0.45	Erratic driving in Tier-3 cities causes variance
Narrow	Alex and Isaac (2015) [44] (Simulation)	Sim. (7m)	Mod. Area	40.0%	~0.15	Simulation underestimates physical blockage
Wide	Patel and Dhamaniya (2021) [47] (Ahmedabad)	A-01	Time Occ.	63.2%	0.13–0.32	In wide roads, PCE values stabilize
Wide	Maddu et al. (2025) [15] (Pune)	A-03	Time Occ.	65.2%	0.20–0.26	Tier-1 results overlap with Patel's findings
Wide	Alex and Isaac (2015) [44] (Simulation)	Sim. (10.5m)	Mod. Area	40.0%	~0.24	PCE increases due to higher speeds
Wide	Sun et al. (2022) [56] (Guiyang, China)	Straight	Travel-Time	1.0%	0.50	Lane discipline prevents swarming
Wide	Sun et al. (2022) [56] (Guiyang, China)	Straight	Speed-Based	1.0%	0.74	Speed-based method yields higher PCE

Note: Narrow: ~7.0 m; Wide: >10.0 m. Abbreviations: 2W: Two-Wheeler; Occ.: Occupancy; Mod.: Modified; Sim.: Simulation.

Table 14. Comprehensive controlled comparison of heavy vehicle PCE values.

Width	Study (City)	Approach	Method	% HV	PCE	Key Finding
Narrow	Patel and Dhamaniya (2021) [47] (Ahmedabad)	A-13	Time Occ.	5.38%	3.11–5.38	Even moderate HV creates severe blockage
Narrow	Maddu et al. (2025) [15] (Guwahati)	A-11	Time Occ.	1.28%	3.46–4.52	Minimal HV presence still yields high PCE
Narrow	Alex and Isaac (2015) [44] (Simulation)	Sim. (7.0m)	Mod. Area	10.0%	~2.70	Simulation fails to capture static blockage
Wide	Patel and Dhamaniya (2021) [47] (Ahmedabad)	A-11	Time Occ.	12.31%	4.76–6.93	High HV concentration creates impedance
Wide	Maddu et al. (2025) [15] (Guwahati)	A-05	Time Occ.	5.45%	3.46–4.30	Bus PCE remains high (>3.5) regardless of width
Wide	Alex and Isaac (2015) [44] (Simulation)	Sim. (10.5m)	Mod. Area	10.0%	~3.90	PCE increases in wide roads
Wide	Sun et al. (2022) [56] (Guiyang, China)	Straight	Travel-Time	5.0%	2.95	Bus behaves as “large car” with lane discipline
Wide	Sun et al. (2022) [56] (Guiyang, China)	Straight	Speed-Based	5.0%	3.31	Speed-based captures momentum loss

Note: Narrow: ~5.5–7.0 m; Wide: >10.0 m. Abbreviations: HV: Heavy Vehicle; Occ.: Occupancy; Mod.: Modified; Sim.: Simulation.

Thirdly, Sun et al.'s [56] data from Guiyang, China presents a contrasting case that must be interpreted carefully. With a very low two-wheeler proportion (1.0%), the reported PCE values (0.50–0.74) are significantly higher than Indian studies where two-wheeler proportions exceed 70%. This finding aligns with Patel and Dhamaniya's [47] conclusion that an increased proportion of small vehicles forms good operating conditions for these vehicles themselves, consequently reducing their time occupancy ratio; however, it increases time occupancy ratio for large vehicles.

As shown in Table 14, Sun et al. [56] reports the lowest heavy vehicle PCE values (2.95–3.31) among all field studies, confirming the inverse relationship: when small vehicle proportion is low, large vehicles experience better operating conditions, resulting in lower PCE values. Additionally, strict lane discipline in Chinese traffic prevents seepage behavior

regardless of proportion, as two-wheelers are expected to occupy full lane width rather than filter between larger vehicles.

The simulation study by Alex and Isaac [44] consistently underestimated PCEs compared to field data, specifically in narrower approaches.

For heavy vehicles, although the two field studies report values greater than 3.0 regardless of approach width, Sun et al. [56] reported 2.95 with Travel-time/length method and 3.31 with speed/length method, confirming significant impedance in non-lane-based mixed heterogeneous traffic. They concluded that while speed-based methods capture instantaneous vehicle dynamics, travel-time methods may represent the standard PCE definition more accurately as they directly measure time resources occupied at the intersection.

Although Alex and Isaac's [44] TRAFFICSIM model was specifically designed to simulate non-lane-based Indian traffic conditions, it yields lower heavy vehicle PCE values (~ 2.70) compared to recent field studies (3.46–4.52). This discrepancy may be attributed to two factors: either simulation models inherently struggle to capture the full extent of chaotic interactions in heterogeneous traffic, or traffic conditions in Indian cities have become more congested and aggressive over the decade between the simulation study (2015) and recent field observations (2021–2025).

4.3.5. Optimization Method

Radhakrishnan and Mathew [2] and Mondal and Gupta [48] both employed dynamic optimization minimizing Theil's inequality coefficient, yet their PCE values diverge notably for certain vehicle types (Table 15).

Table 15. Cross-study comparison of PCE values using the optimization method.

Study	2W	3W	Car	Bus	Truck	LCV	Key Finding
Radhakrishnan and Mathew (2011) [2] (Jaipur, Bangalore, Trivandrum)	0.34	1.88 (auto), 1.46 (cycle)	1.00	–	3.90	1.23	Optimum PCEs yield more consistent flow rates
Mondal and Gupta (2019) [48] (Allahabad, India)	0.36	1.09	1.00, 1.46 (Big)	2.90	–	1.90	Saturation flow 1908 PCEs/h aligns with HCM (1900)

Deviations in the results are attributable to differences in environmental conditions and methodological implementation across studies.

Saturated Green Period Filtering (ANOVA): Mondal and Gupta [48] did not use the entire green duration in their analysis; instead, they used “saturated green intervals” (e.g., between 12 and 18 s) identified through one-way ANOVA tests to determine where flow was truly stabilized. On the other hand, Radhakrishnan and Mathew [2] divide the green phase into five-second intervals and consider all intervals above a certain threshold (3 PCE/5 s) as saturated. Mondal and Gupta [48] thus focused on a narrower and purer saturation window than Radhakrishnan and Mathew [2], which may have resulted in lower estimates of vehicle impacts, particularly for three-wheelers.

Classification details of the vehicles: Mondal and Gupta [48] classify standard passenger cars into two categories “standard car” and “big car” (1.46 PCE), whereas Radhakrishnan and Mathew [2] groups all passenger cars into a single class.

Differences in city and driver behavior: Radhakrishnan and Mathew [2] collected data from three cities: Jaipur, Bangalore, and Trivandrum, whereas Mondal and Gupta [48] collected all data from Allahabad.

It is noteworthy that the value of 1.88 in Radhakrishnan and Mathew [2] drops to 1.09 in Mondal and Gupta [48]. This suggests that either the area occupied by three-wheelers in Mondal and Gupta's [48] study region is very similar to that of a standard car, or they

impede traffic flow much less during saturated conditions (i.e., saturated area), as opposed to those studied by Radhakrishnan and Mathew [2]. The opposite pattern is observed for LCVs: Mondal and Gupta [48] reported a value of 1.90, considerably higher than Radhakrishnan and Mathew [2] (1.23), suggesting that light commercial vehicles create almost twice the “load” compared to automobiles in Allahabad traffic. This difference may be due to the physical dimensions of these types of vehicles in the two regions, or their speed when traveling through intersections in Allahabad is much slower than in other areas.

4.3.6. Capacity-Based Method

Among the capacity-based studies, Barna et al. [51] reported notably higher PCE values than Kollár [50] (e.g., 2.63 vs. 1.80 for semi-trailers; Table 16), despite both studies examining signalized intersection conditions. Barna et al. [51] indicated that this difference is due to the following.

- Geometric constraints: Although subject to signal control, Barna et al. [51] included circular movements, which impose greater impedance on longer vehicles compared to the standard four-leg intersection geometry examined by Kollár [50].
- Capacity: Both studies employed VISSIM microsimulation to derive PCE values; however, they adopted distinct approaches to defining the saturation point. Kollár [50] found that PCE values for signalized intersections are dynamic in nature and relate to varying levels of traffic volume, they increase proportionately as volume increases. Thus, Kollár [50] suggested using PCE values calculated at the maximum traffic volume conditions possible to allow for design of adequate signal timing to meet the demand of peak traffic volumes and to reduce the risk of underestimating the impact of large vehicles during those high-traffic volume periods. On the other hand, Barna et al. [51] defined a more quantitative measure of saturation based upon average vehicle delay. They determined that saturation occurs when average delay is greater than or equal to the duration of a signal cycle of 80 s; this indicates that all available capacity has been used and that an impending traffic congestion situation will exist. Additionally, Barna et al. [51] improved the statistical reliability of their results by implementing a 95% confidence interval to the calculated PCE values.

Table 16. Cross-study comparison of PCE values using capacity-based method.

Study	Bus	Truck	Key Finding
Kollár (2014) [50] (Simulation)	–	Heavy-duty trailer: 1.50, semi-trailer: 1.80, truck-trailer: 2.63	PCE values increase proportionally with traffic volume
Barna et al. (2018) [51] (Simulation)	2.34 (solo, 11.5 m), 3.34 (articulated, 18.5 m)	1.83 (heavy truck, 10.2 m), 2.63 (semi-trailer, 16 m)	Buses exert higher impact than current standards suggest

4.3.7. Queue-Based Method

Two distinct queue-based approaches are represented. Mohan and Chandra’s [52] queue clearance rate (QCR) method derives PCE from acceleration characteristics during queue discharge, optimizing values to minimize clearance rate variance. Jithender and Sushmitha’s [80] queue length model bases PCE values on physical vehicle dimensions (width) and the longitudinal and lateral standstill distances maintained while queuing. This approach emphasizes spatial occupancy rather than dynamic performance. These methodologies differ significantly due to their respective methodological frameworks, as evidenced by significant differences in the estimation of PCEs for motorcycles (Table 17): Mohan and Chandra [52] have estimated PCEs for motorcycles to be between 0.10 and 0.25, indicating

high levels of filtering ability and acceleration rates; Jithender and Sushmitha [80] have estimated a PCE of 0.60, based on the physical space consumed by motorcycles.

Similarly, heavy vehicles show considerable divergence: Mohan and Chandra [52] estimated PCEs for truck traffic to vary by up to 74% depending on the mix of vehicles in the stream (between 2.49 and 4.35); Jithender and Sushmitha [80] estimated a fixed value of 3.8 for all types of heavy vehicles.

Jithender and Sushmitha [80] further demonstrate volume sensitivity, with PCE values increasing beyond 1500–2000 veh/h. Clearance-based approaches better capture operational efficiency, while occupancy-based methods, though tending to yield higher values, may be more suitable for planning capacity under congested conditions.

Table 17. Cross-study comparison of PCE values using queue-based method.

Study	2W	3W	Car	Bus	Truck	LCV	Key Finding
Mohan and Chandra (2017) [52] (Simulation, India)	0.10–0.25	0.19–0.53	1.00	3.65–5.06	2.49–4.35	1.09–2.08	Queue clearance rate method
Jithender and Sushmitha (2024) [80] (Warangal, India)	0.60	0.80	1.00	3.80	3.80	2.20	Queue length (standstill distance ratio)

5. Discussion

This review represents the first systematic assessment of PCE estimation methods specifically at urban signalized intersections. The synthesis of 40 peer-reviewed studies from 1978 to 2025 reveals that PCE values vary substantially across studies and countries. This variation is unlikely to be explained solely by measurement inconsistencies; rather, PCE varies systematically with traffic conditions, estimation method, and local driving behavior. This raises a fundamental question: whether intersection capacities and signal timings derived from the fixed PCE values in guidelines such as the HCM and IRC are sufficiently accurate, or whether site-specific dynamic PCE formulations are needed.

The reviewed studies predominantly employed dynamic estimation approaches: 72.5% used dynamic methods, and this proportion increased from 50% before 2000 to 83% between 2016 and 2025 ($\chi^2 = 8.10$, $df = 1$, $p = 0.004$). This trend reflects a growing recognition that fixed values fail to capture the context-dependent nature of vehicle equivalency. Many of these studies evaluated their dynamically estimated PCE values against the static values prescribed by national guidelines such as the HCM [10], IRC [12], and IHCM [11]. The deviations are often substantial: Asaithambi et al. [1] found that their Chennai-based PCE values differed considerably from IRC specifications, while Sugiarto et al. [77] reported a 60% deviation from the IHCM value for motorized rickshaws in Banda Aceh. For trucks, the IRC assigns a fixed value of 3.0, yet truck PCE values reported across the reviewed studies ranged from 1.13 [14] to 4.35 [52]. More striking is the variation within a single country. In India, Radhakrishnan and Mathew [2] estimated LCV PCE at 1.23 from data collected in Jaipur, Bangalore, and Trivandrum, whereas Mondal and Gupta [48] reported 1.90 for Allahabad. The cross-study comparison of area/occupancy methods further revealed a critical divergence between Tier-1 and Tier-3 cities even under similar geometric conditions. These findings confirm that PCE is not merely country-specific but city-specific, and that traffic behavior is sufficiently variable to render any single static value inadequate for representing local conditions. Consequently, intersections designed using a single fixed value may be either over-designed or under-designed.

Across the reviewed studies, three traffic-related factors were found to significantly affect PCE values. First, traffic volume exerts a non-linear effect on PCE. At lower volumes, vehicles maintain larger headways and PCE values tend to increase; at higher volumes, smaller vehicles exploit gaps more effectively, reducing their PCE, while larger vehicles

continue to impose greater impedance [48,52]. This implies that PCE values calibrated at one volume level may produce substantial errors when applied at another. Second, road width affects PCE values in a counter-intuitive manner. Under weak lane discipline, wider approaches allow vehicles to spread out rather than forming compact queues, resulting in larger discharge headways and higher PCE values for all vehicle types [15,47]. The cross-study comparison of area/occupancy methods confirmed this pattern: two-wheeler PCE values showed greater variability at narrower approaches (0.14 to 0.45) than at wider ones (0.20 to 0.26). Third, traffic composition significantly influences vehicle interactions. As the proportion of a specific vehicle category increases, its PCE value typically decreases; Patel and Dhamaniya [47] attributed this to the improved operating conditions formed by dominant vehicle groups, and Maddu et al. [15] quantified the relationship, showing that motorcycle PCE decreased from 0.32 to 0.14 as motorcycle proportion increased from 30% to 72%.

Each of the seven estimation methods identified in this review has its own measurement framework, but their suitability largely depends on data collection feasibility in the field. For lane-based or moderately mixed traffic, headway-based ($n = 12$) and regression-based ($n = 13$) methods remain the most widely employed and well-validated approaches, as they rely on measurable individual vehicle headways during queue discharge. However, in highly heterogeneous environments with weak lane discipline, where vehicles do not follow one another in discrete lanes, these methods face fundamental limitations. Area/occupancy methods were developed specifically to address this gap by accounting for the two-dimensional space vehicles occupy on the roadway; notably, 75% of occupancy-based studies originated from South Asia (Table 5), suggesting that this approach is emerging as a region-specific methodological response to local traffic conditions.

The remaining methods emerged chronologically as responses to the limitations of headway-based approaches. Delay-based methods (first introduced in 1984) shifted the focus from headway consumption to operational performance across the entire queue, though measuring delay is more complex and costly than measuring headway [39]. Optimization methods addressed the circular dependency between PCE and saturation flow through iterative algorithms, but their results are sensitive to how the saturated green period is defined: Radhakrishnan and Mathew [2] and Mondal and Gupta [48] both used Theil's coefficient, yet their LCV PCE values differed substantially (1.23 vs. 1.90), largely due to differences in green phase segmentation. Queue-based methods, the most recent addition (2017), derive PCE from discharge characteristics without requiring saturation flow measurement, making them applicable to heterogeneous traffic [52,80]. Even within a single study, method selection affects results: Sun et al. [56] applied both travel-time and speed-based approaches to the same intersections and obtained different PCE values (0.50 vs. 0.74 for two-wheelers; 2.95 vs. 3.31 for heavy vehicles). These comparisons suggest that relying on a single estimation method may introduce methodological bias. Most studies already validate their results against headway-based estimates as a benchmark, and this practice of cross-method comparison should be encouraged to provide a more robust understanding of PCE values.

Beyond the current state of practice, the transportation environment is evolving in ways that will create additional challenges for PCE estimation. Connected and Autonomous Vehicles (CAVs) exhibit fundamentally different driving characteristics compared to human-driven vehicles, including shorter and more consistent headways, smoother acceleration profiles, and platooning capabilities [84,85]. Evidence from freeway contexts suggests that CAVs can substantially alter capacity dynamics, including reported reductions in truck PCE of approximately 34% under platooning [86]. For signalized intersections specifically, Adebisi et al. [87] developed capacity adjustment factors within the HCM framework,

demonstrating that CAV technologies can increase saturation flow rates through reduced follow-up headways. However, existing PCE estimation methods were developed entirely for human-driven vehicles and have not yet been validated for mixed traffic environments with varying CAV penetration rates. As these rates increase, mixed traffic combining autonomous and human-driven vehicles will create a new form of heterogeneity that differs fundamentally from the conventional mixed traffic that has been the focus of existing research.

This review has certain limitations that should be acknowledged. First, only studies published in English were included; a substantial body of potentially relevant research may exist in other languages, particularly in Chinese, Japanese, Korean, and other Asian languages, given the significant concentration of PCE research in Asian countries. This language restriction may have excluded valuable methodological contributions and regional findings. Second, the focus on peer-reviewed journal articles means that conference papers and grey literature containing innovative methodologies were not captured. Third, the geographic distribution of included studies is heavily concentrated in Asia ($n = 24$; $\chi^2 = 26.60$, $df = 3$, $p < 0.001$), with limited representation from Europe and Africa, which restricts generalizability to those regions.

Future research should address several important frontiers. The development of standardized dynamic PCE models for typical mixed-traffic conditions remains a priority, as does the investigation of gradient effects on PCE at signalized intersections, a factor that none of the 40 reviewed studies examined despite its potential significance for intersections in hilly terrain. The geographic concentration of studies in Asia highlights a need for research in underrepresented regions, particularly Europe and Africa, where different traffic compositions, infrastructure standards, and driving behaviors may yield different PCE characteristics. There is also an emerging need for PCE estimation frameworks that accommodate CAV technologies and their interactions with human-driven vehicles across different penetration rates. Finally, comparative studies that apply multiple estimation methods to the same intersection under identical traffic conditions would provide valuable insight into the degree to which reported PCE variability reflects true differences in traffic behavior versus methodological artifacts.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/futuretransp6010041/s1>.

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Abbreviations

The following abbreviations are used in this manuscript:

2W	Two-Wheeler
3W	Three-Wheeler
ANOVA	Analysis of Variance
ATCS	Area Traffic Control System
AW	Approach Width
CAVs	Connected and Autonomous Vehicles
CT	Combination Truck
CV	Coefficient of Variation
D-PCE	Delay-Based Passenger Car Equivalent
DOI	Digital Object Identifier
HCM	Highway Capacity Manual
HGV	Heavy Goods Vehicle
HV	Heavy Vehicle
IHCM	Indonesian Highway Capacity Manual
IRC	Indian Roads Congress
LB	Lane-Based
LCV	Light Commercial Vehicle
LOS	Level of Service
LP	Linear Programming
MC	Motorcycle
NLB	Non-Lane-Based
PCE	Passenger Car Equivalent
PCU	Passenger Car Unit
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QCR	Queue Clearance Rate
SFR	Saturation Flow Rate
SUT	Single-Unit Truck
SUV	Sport Utility Vehicle
UAV	Unmanned Aerial Vehicle
VISSIM	Verkehr In Städten–SIMulationsmodell (Traffic in Cities–Simulation Model)

Appendix A. Database Search Strategies

The following search queries were executed across three databases on 24 November 2025. While a consistent conceptual structure was maintained across all searches, syntax adaptations were necessary to accommodate the specific requirements and limitations of each database interface.

Appendix A.1. Scopus

Search Query:

```
( ( TITLE-ABS-KEY ( ‘passenger car unit’ OR ‘passenger car
equivalent’ OR ‘passenger car equivalency’ OR PCE OR PCU OR
‘equivalency factor’ OR ‘conversion factor’ OR ‘vehicle
equivalency’ OR ‘saturation flow’ OR ‘dissipating flow’ OR
```

‘discharge flow’ OR ‘discharge rate’ OR ‘flow ratio’ OR
‘flow ratios’ OR ‘flow equivalency’ OR ‘start-up behavior’
OR ‘lost time’ OR ‘traffic heterogeneity’ OR ‘mixed traffic
conditions’ OR ‘vehicle composition’)) AND (TITLE-ABS-KEY
(‘traffic flow’ OR ‘traffic operations’ OR ‘traffic
performance’ OR ‘capacity analysis’ OR ‘capacity estimation’
OR headway OR ‘headway distribution’ OR ‘gap acceptance’ OR
‘driver behavior’ OR ‘speed-flow-density’ OR ‘fundamental
diagram’ OR ‘queue formation’ OR ‘discharge characteristics’
OR ‘flow characteristics’ OR ‘movement patterns’))) AND
(TITLE-ABS-KEY (roundabout OR ‘rotary intersection’ OR
‘unsignalized intersection’ OR ‘unsignalised intersection’
OR ‘signalized intersection’ OR ‘signalised intersection’
OR ‘weaving section’ OR ‘merging area’ OR freeway OR
expressway OR ‘highway sections’ OR ‘urban corridors’ OR
‘rural roads’ OR ‘urban roads’ OR ‘arterial roads’ OR
‘bus lanes’ OR ‘mixed-use corridors’ OR ‘capacity drop’ OR
‘critical gap’ OR ‘entry capacity’ OR ‘follow-up headway’)))

Search Fields: Title, Abstract, Keywords

Date of Search: 24 November 2025

Appendix A.2. Web of Science

Search Query:

(((((ALL=(passenger car unit)) OR
ALL=(passenger car equivalent)) OR ALL=(passenger car
equivalency)) OR ALL=(PCE)) OR ALL=(PCU)) OR
ALL=(equivalency factor)) OR ALL=(conversion factor)) OR
ALL=(vehicle equivalency)) OR ALL=(saturation flow)) OR
ALL=(dissipating flow)) OR ALL=(discharge flow)) OR
ALL=(discharge rate)) OR ALL=(discharge rates) OR
ALL=(flow ratio)) OR ALL=(flow ratios))) OR
ALL=(flow equivalency)) OR ALL=(start-up behavior)) OR
ALL=(lost time)) OR ALL=(traffic heterogeneity)) OR
ALL=(mixed traffic conditions)) OR ALL=(vehicle composition)
AND
(((((ALL=(‘traffic flow’)) OR
ALL=(‘traffic operations’)) OR ALL=(‘traffic performance’))
OR ALL=(‘capacity analysis’)) OR ALL=(‘capacity estimation’))
OR ALL=(‘headway’)) OR ALL=(‘headway distribution’)) OR
ALL=(‘gap acceptance’)) OR ALL=(‘driver behavior’)) OR
ALL=(‘speed-flow-density’)) OR ALL=(‘fundamental diagram’))
OR ALL=(‘queue formation’)) OR ALL=(‘discharge characteristics’))
OR ALL=(‘flow characteristics’)) OR ALL=(‘movement patterns’))))
AND
(((((ALL=(roundabout)) OR
ALL=(rotary intersection)) OR ALL=(unsignalized intersection))
OR ALL=(unsignalised intersection)) OR
ALL=(signalized intersection)) OR
ALL=(signalised intersection)) OR ALL=(weaving section)) OR

ALL=(merging area)) OR ALL=(freeway)) OR ALL=(expressway)) OR
 ALL=(highway sections)) OR ALL=(urban corridors)) OR
 ALL=(rural roads)) OR ALL=(urban roads)) OR
 ALL=(arterial roads)) OR ALL=(bus lanes)) OR
 ALL=(mixed-use corridors)) OR ALL=(capacity drop)) OR
 ALL=(critical gap)) OR ALL=(entry capacity)) OR
 ALL=(follow-up headway)

Search Fields: All Fields

Date of Search: 24 November 2025

Appendix A.3. ScienceDirect

Search Query: ScienceDirect imposes a maximum limit of eight Boolean connectors.

((‘passenger car unit’ OR ‘passenger car equivalent’ OR
 ‘passenger car equivalency’ OR PCE OR PCU) AND
 (‘mixed traffic’ OR ‘heterogeneous traffic’ OR ‘traffic flow’))

Search Fields: Title, Abstract, Keywords

Date of Search: 24 November 2025

Appendix B. Extended Methodological Details

The following section presents the mathematical formulation, derivation, and data collection protocols associated with the methodologies discussed in Section 2. The rationale for including these detailed methods is to provide the reader with enough detail to understand how the methodology was used to conduct the review while maintaining the clarity of the main body of the text.

Appendix B.1. Headway Ratio Method: Additional Formulations and Methodologies

Appendix B.1.1. Independence Assumption and Reference Headway Definition

In early applications of the headway ratio method, data collection typically recorded only the vehicle type and its corresponding headway, without systematically documenting the type of the leading vehicle. The lack of indication regarding the leading vehicle implies an implicit independence assumption: that the headway of a given vehicle depends only on the characteristics of the current vehicle, and not the type of the vehicle ahead of it. The implication of this assumption is that if a truck followed a car, the headway of the truck should be the same if it follows another truck. Steuart and Shin [81] demonstrated that the leading vehicle type significantly affects headway values. For instance, a passenger car following a truck tends to maintain a longer headway than when following another passenger car, due to factors such as reduced visibility and the tendency to keep greater distance from larger vehicles. This indicates that the recording of both vehicle types and enabling vehicle-pair analysis is a necessity.

Appendix B.1.2. Vehicle Pairing Approach

Kimber et al. [7] applied the headway correction procedure originally developed by Scraggs [28] based on measuring headways for all vehicle-pair combinations to ensure that the effect of heavy vehicles on headways is independent of the preceding and following vehicle classes. This correction method minimizes the sum of squared deviations while satisfying the condition that (Equation (A1))

$$h_{c-c} + h_{x-x} = h_{x-c} + h_{c-x} \quad (\text{A1})$$

where

- h_{c-c} is the headway of a car following a car,
- h_{x-x} is the headway of vehicle type x following another vehicle of type x ,
- h_{c-x} is the headway of vehicle type x following a car, and
- h_{x-c} is the headway of a car following vehicle type x .

When this condition is not satisfied, a correction factor is applied using the least squares method to obtain adjusted headways that satisfy the independence condition. The corrected PCE is then calculated from these adjusted headways.

This correction procedure has been widely adopted in subsequent studies conducted in various countries including Bangladesh [63,66], Gaza Strip [67], and India [1], particularly in contexts where the leading vehicle effect is statistically significant.

Appendix B.1.3. Data Collection Protocols for Field Headway Measurement

Reliable PCE estimation using the headway ratio method requires consistent measurement protocols. Several methodological considerations have developed over the decades of research.

Reference Points for Headway Measurement

Time headway can be defined as the time interval between successive vehicles passing a reference point. Steuart and Shin [81] measured headways by two different reference point approaches. The first one is rear axle to rear axle; with this approach, they investigated whether vehicles follow small cars more closely. With this measurement strategy, full-sized cars were used as the control group, minimizing the influence of vehicle length on headway measurement. To examine the converse hypothesis—whether small cars follow other vehicles more closely—headways were measured from the front axle of a full-sized car to the front axle of a following passenger car. The researchers found this differentiation to be very important in the development of PCE models because selecting a reference point (e.g., the front or rear bumper or the front or rear axle) could systematically alter the headway measurements, particularly when comparing vehicles of significantly different sizes. If such studies fail to account for this variation, the influence of vehicle type will likely be confused with variations related to vehicle size.

Studies vary in their specific reference points: front bumper crossing the stop line [72–74], front axle crossing [65], rear axle crossing [63,66], and rear bumper crossing [7]. While the choice of reference point affects absolute headway values, it does not affect PCE ratios when applied consistently across all vehicle types.

Elimination of Start-Up Lost Time Effects

Drivers must first perceive the change of the traffic signal from red to green, and then take action by pushing down on the gas pedal while pulling up on the brake pedal to begin moving. The lead vehicle in the queue has a relatively larger headway than the vehicle immediately behind it because the second vehicle driver's perception–reaction time partially overlaps with that of the leading vehicle, and the vehicle benefits from a greater acceleration distance. The lost time due to a vehicle's perception and reaction time and the vehicle's speed/acceleration through the intersection, the total additional time it takes for the first few vehicles to cross the stop line, is referred to as “Start-up Lost Time” (SLT), or l_1 , as shown in Figure A1 [88].

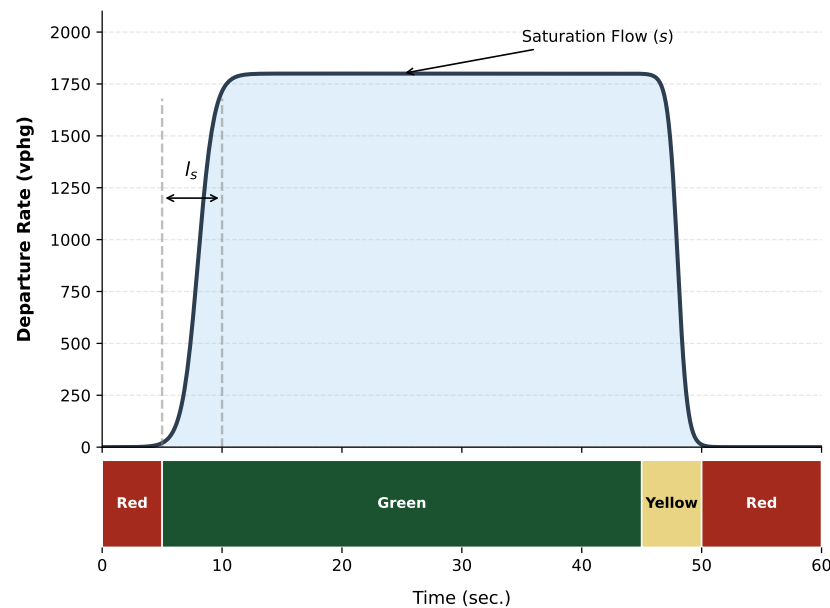


Figure A1. Saturation flow rate and start-up lost time at signalized intersections. Adapted from Molina et al. [88].

It was first observed by Greenshields et al. [27] that headways were stabilized after the first few vehicles in the platoon and that headways of subsequent vehicles were found to be near constant at a saturation headway of approximately 2.1 s. This pattern was illustrated by Molina et al. [88] in Figure A2 [88], showing that saturation headways are reached from position 5 onward in the queue.

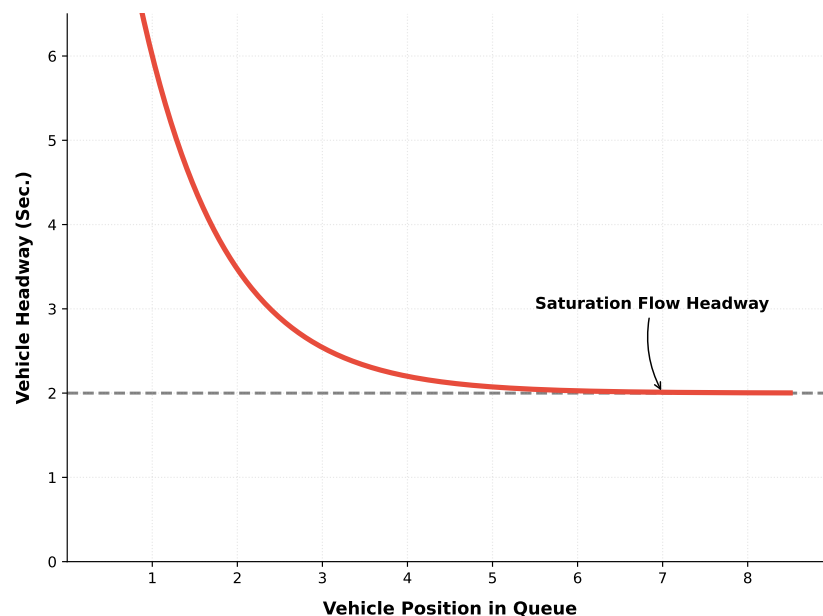


Figure A2. Vehicle headway variation by queue position. Adapted from Molina et al. [88].

The Highway Capacity Manual [25] recommends excluding the first four vehicles from saturation flow measurements to eliminate SLT effects. Saturation headways should be calculated based on vehicles in positions 5 through 8 or further in the queue. Tsao and Chu [89] adopted this convention in their study of two intersections in Taipei, Taiwan, measuring only headways from the fifth vehicle onward. However, Li and Prevedouros [90] found that the minimum headway was not reached until the 9th

to 12th vehicle at their Honolulu study site. Similarly, Limanond et al. [91] reported that the vehicle position at which saturation headway is first sustained varied between the 5th and 10th vehicle depending on traffic intensity and time of day at a Bangkok intersection. These findings suggest that the transition point between start-up transient and saturated conditions is not fixed but may vary with local traffic characteristics.

Washburn and Cruz-Casas [65] attributed the start-up lost time to the first four vehicles in a queue and developed a model for estimating start-up lost time as a function of truck type percentages (Equation (A2)):

$$SLT = 2.5 + 5.0 \cdot P_{ST} + 9.0 \cdot P_{MT} + 15 \cdot P_{LT} \quad (A2)$$

where

- SLT is start-up lost time in seconds for the first 4 cars of the queue.
- P_{ST} , P_{MT} , P_{LT} are the proportions of small, medium, and large trucks in the traffic.

For a passenger-car-only queue, start-up lost time measured as 2.5 s, and for a mixed queue as in Figure A3, the start-up lost time would be 5.77 s.

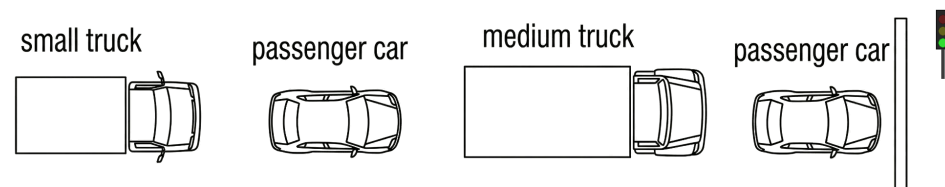


Figure A3. A mixed queue composition derived from Washburn and Cruz-Casas [65].

For situations where only overall truck percentage is available, a simplified model was proposed (Equation (A3)):

$$SLT = 2.5 + 10 \cdot P_T \quad (A3)$$

where P_T is the total truck proportion.

Suweda and Wedagama [76] concluded that in motorcyclist-dominated traffic conditions, it was necessary to exclude the first five vehicles in order to remove both the effect of reaction time due to start-up and the effect of acceleration since the smaller size and different acceleration characteristics of motorcyclists can change the stabilization process.

Another aspect that affects the SLT is the technical condition of vehicles; specifically, the acceleration capability can influence PCE values. Fornalchyk et al. [69] investigated this relationship, noting that during five years of intense operation, vehicle acceleration properties can deteriorate by up to 25%, resulting in slower departure from the stop line and consequently longer headways.

Saturated Cycle Requirements

To ensure that measured headways reflect capacity conditions, only fully saturated cycles should be included in the analysis. A saturated cycle is one in which the queue is not completely discharged by the end of the green interval, ensuring continuous demand throughout the measurement period. Washburn and Cruz-Casas [65] recommend that a minimum of an eight-vehicle-long queue be maintained on each approach to meet this condition, consistent with HCM [25]. More recent research by Ghanim and Abu-Lebdeh [79] has considered oversaturated conditions (i.e., demand greater than supply for extended time frames), and found that PCE values exhibit markedly different behaviors under these extreme congestion conditions. PCE values exhibit a non-linear, non-monotonic relationship with truck percentage under oversaturation. Using VISSIM simulation calibrated with

field data, they found that PCE increased from 2.13 at 5% truck proportion to a peak of 2.36 at 15%, then decreased to 2.19 at 40%. This pattern suggests that at very high truck proportions, the traffic stream becomes more homogeneous, reducing the relative disadvantage of individual trucks. Based on their comprehensive analysis, Ghanim and Abu-Lebdeh [79] recommended a PCE value of 2.25–2.30 for trucks at oversaturated signalized intersections, higher than the HCM default of 2.0 for through movements.

Strip-Based Measurement for Non-Lane-Based Traffic

In heterogeneous traffic conditions where vehicles do not follow a strict lane discipline, traditional headway measurements that rely on lane discipline become impractical. Vehicles such as motorcycles will often ride alongside much larger vehicles and/or will occupy small gaps in front of or behind a larger vehicle. During the red light phase, smaller vehicles may also be positioned directly in front of the stop line. A strip-based method was developed by Suweda and Wedagama [76] and Kariyana et al. [78] to address the challenges of measuring headways in non-lane-based mixed traffic conditions. In this approach, each lane is segmented into "strips" generally the same width as a motorcycle (approximately 0.75 m), and headways are measured from one strip to another, enabling systematic measurement even where motorcycles and larger vehicles share roadway space in the absence of lane discipline.

Simulation as a Data Generation Tool

Field data collection limitations have led some researchers to employ simulation as a complementary data generation tool. Washburn and Cruz-Casas [65] developed a custom simulation program based on the Modified Pitt car-following model [92], calibrated with field data from six intersections. Similarly, Fornalchuk et al. [69] utilized VISSIM microsimulation to generate headway data for vehicles with varying acceleration capabilities, enabling systematic investigation of vehicle technical condition effects. Ghanim and Abu-Lebdeh [79] also employed VISSIM, calibrated with field data from oversaturated intersections in Kentucky. These studies demonstrate that simulation, when properly calibrated with field data, can effectively extend the range of conditions for which PCE values can be estimated.

Environmental and Weather Effects on Headway Measurement

Environmental site characteristics and weather conditions can influence headway measurements and consequently PCE values. Roadside activities such as bus stops, taxi ranks, and fuel stations located near intersections can disrupt vehicle discharge by creating merging and diverging movements. Obiri-Yeboah et al. [82] investigated this effect in Kumasi, Ghana, and found that truck PCE increased from 2.25 to 3.05 and medium vehicle PCE increased from 1.35 to 1.65 at intersections with roadside friction compared to friction-free locations. These differences were attributed to vehicles slowing down due to merging and diverging traffic activities created by these roadside activities.

Weather conditions also affect headway measurements. Zahiri and Chen [72] compared PCE values on sunny and rainy days and found that mean headways increased during rain due to reduced visibility and wet pavement conditions. SUVs PCE values increased from 1.26 on sunny days to 1.31 on rainy days.

Appendix B.2. Regression Method: Equations for Synchronous and Asynchronous Counting

Appendix B.2.1. Additional Equations for Synchronous Regression Method

Kimber et al. [7] examined only the saturation flow region where vehicles depart the intersection at a constant rate. During the green phase at a signalized intersection, the

departure rate follows three distinct phases: an initial acceleration phase when vehicles start moving, a central plateau where flow reaches its maximum steady value (saturation flow), and a final phase during amber when vehicles begin to stop, departing from the intersection at decreasing rates. By restricting analysis to the central plateau region only, Kimber eliminated the start-up lost time effects at the beginning of green (when vehicles are still accelerating) and end lag effects during amber (when some vehicles continue to depart). Therefore, Kimber et al. [7] developed the simplified version of Branstons and van Zuylen's equation as presented by Equation (A4).

$$\tau = \sum \eta_i n_i + \varepsilon \quad (\text{A4})$$

where

- τ : Length of counting period, beginning and ending with a vehicle departure (dependent variable).
- η_i : Population mean headway of vehicle type i .
- n_i : Number of vehicles of class i departing during counting period.
- a_i : Regression estimate of η_i .
- ε : Error term.

This approach requires careful data collection: counting periods must begin after the initial acceleration phase is complete and end before the amber phase begins. This ensures observations represent pure saturation flow conditions without transient effects.

From the regression model $\tau = \sum \eta_i n_i + \varepsilon$, the regression estimates (a_i) represent the average headway for each vehicle type. The PCE value is calculated as the ratio of any vehicle type's headway to the passenger car headway [7,33]:

$$PCE_i = \frac{a_i}{a_{car}} = \frac{\eta_i}{\eta_{car}} \quad (\text{A5})$$

where

- a_i (or η_i) = regression estimate of headway for vehicle type i .
- a_{car} (or η_{car}) = regression estimate of headway for passenger cars.

For example, if $a_{bus} = 3.2$ s and $a_{car} = 2.0$ s;

then, $PCE_{bus} = 3.2/2.0 = 1.6$.

Appendix B.2.2. Additional Equations for Asynchronous Regression Method

Kimber et al. [7] provided a simplified form for fixed interval counting. When T is constant, the $\beta_0 T$ term becomes a constant intercept:

$$n_1 = \beta_0'' - \sum \beta_i'' n_i + \varepsilon'' \quad (\text{A6})$$

where

- $\beta_0'' = \beta_0 T$ (constant intercept).
- $\beta_i'' = PCE$ values (equivalent to β_i).

In the asynchronous method, the regression coefficients directly represent PCE values:

$$PCE_i = \alpha_i = \beta_i = \beta_i'' \quad (\text{A7})$$

This is because the equation expresses how many passenger cars are "displaced" by each vehicle of type i . For instance, if $\alpha_{bus} = 2.5$, it means each bus displaces 2.5 passenger cars in terms of capacity.

Appendix B.2.3. Data Collection Protocols

The regression method requires careful determination of counting intervals and saturation conditions. Branston and van Zuylen [33] used fixed 6 s intervals for vehicle counting.

For regression validity, data collection must be restricted to saturated green time, defined as periods when queue presence is continuous and traffic demand exceeds capacity. To operationalize this in heterogeneous traffic, Minh and Sano [16] converted classified vehicle counts into PCE using preliminary values from the literature and defined the saturation threshold as more than 3 PCE per 5-second interval at the stop line. This approach aligns with Thamizh Arasan and Jagadeesh [57], who emphasized that saturation thresholds should be adjusted based on local traffic composition.

Start-up lost time is a critical consideration in data collection for the regression method. In this method, the relationship between saturated green time and vehicle count is typically expressed as

$$t = a_0 + a_1n_1 + a_2n_2 + a_3n_3 \quad (\text{A8})$$

where

- t = saturated green time (seconds).
- n_1, n_2, n_3 = number of vehicles (motorcycle, car, bus).
- a_1, a_2, a_3 = coefficients for each vehicle type (headway).
- a_0 = y-intercept (constant term).

The y-intercept captures the start-up lost time. Branston and van Zuylen [33] reported that this value typically ranges between 3 and 5 s, consistent with the findings of Webster and Cobbe [93].

Appendix B.3. Delay-Based Method: Component Formulations

Appendix B.3.1. D-PCE Method

Benekohal and Zhao [59] developed a Delay-Based Passenger Car Equivalent (D-PCE) methodology building upon the Keller and Saklas [39] approach. The D-PCE (Equation (A9)) is defined as the ratio of the delay generated by a heavy vehicle in a traffic flow to the delay of a vehicle in a traffic stream composed entirely of passenger cars:

$$D\text{-}PCE_i = 1 + \frac{\Delta d_i}{d_0} \quad (\text{A9})$$

where

- Δd_i represents the additional delay caused by vehicle type i , and
- d_0 represents the base delay.

For example, if a platoon consists of 10 passenger cars and they cause 50 s of delay, then the average delay would be $d_0 = 5$ s/veh. However, if a platoon consists of eight cars and two trucks (still total 10 vehicles) and causes 70 s of delay, the additional delay caused by each truck would be $\Delta d = (70 - 50)/2 = 10$ s. Then, the D-PCE factor for the truck is computed as $1 + 10/5 = 3$ [59].

In alternative form (Equation (A10)):

$$D\text{-}PCE = 1 + \frac{d_t - d_0}{p_h \times d_0} \quad (\text{A10})$$

where d_t represents the average delay for the truck case, d_0 represents the average delay for the base case, and p_h represents the percentage of heavy vehicles.

Appendix B.3.2. Queue Position Effect

Rahman et al. [60] identified that previous delay-based studies had not considered the effect of heavy vehicles' queue position on delay. Building upon the delay calculation approach of Gerhart and Wilkinson [94], they incorporated queue position as a factor in PCE estimation, recognizing that vehicles further back in the queue experience proportionally greater delays. In field studies conducted in Yokohama, a 15% delay difference was observed between cases where the heavy vehicle was in the 1st position versus the 10th position in a 10-vehicle queue. This finding demonstrates that PCE values change significantly with queue position for the same percentage of heavy vehicles. The formulation considering queue position is given in Equation (A11):

$$PCE_{LV,j} = 1 + \frac{d_{LG,j}}{D_0} \quad (A11)$$

where

- $PCE_{LV,j}$ is the PCE value of the large vehicle at the j th queue position,
- $d_{LG,j}$ is the increased delay caused by the heavy vehicle at the j th queue position, and
- D_0 is the base delay (passenger car delay).

If the heavy vehicle causes no additional delay ($d_{LG,j} = 0$), then PCE equals 1 (equivalent to a passenger vehicle).

Appendix B.3.3. Data Collection Protocol

Field data used for the delay-based method include complete information on all aspects of traffic (traffic volume by vehicle type, intersection geometric features, and signal timing parameters) [39,59]. Delay is typically measured using the travel time method, where vehicles are tracked from approach entry to exit point through license plate identification or video analysis. After this, delay is calculated as the difference between actual travel time and free-flow travel time [59,71]. When incorporating queue position effects, the position of each vehicle type within the queue must be recorded, requiring observations of queues with at least 10 vehicles to establish reliable patterns [61]. For simulation-based approaches, the model must be calibrated using field-measured delays, with scenarios generated across a range of traffic volumes and heavy vehicle percentages to develop predictive relationships [39,71].

Appendix B.4. Area Occupancy-Based Method: Data Collection Protocol

Data collection for the area occupancy method presents several practical challenges. Video recording from elevated positions is standard practice; however, extracting reliable measurements from these video recordings can be problematic due to issues such as perspective distortion, vehicle occlusion, and shadow interference. The video recording procedure typically involves the use of high-resolution cameras (1080p, 25–30 fps) and software tools such as Kinovea for frame-by-frame analysis [15]. The original speed–area formulation by Chandra and Kumar [18] requires instantaneous speed measurements, which are difficult to obtain in field conditions where vehicles continuously accelerate and decelerate through the intersection. This limitation led researchers to adopt travel time as a more practical surrogate measure [43,45].

A fundamental challenge lies in establishing the baseline condition. The calculation of PCE requires comparison with a 100% passenger car scenario, which is virtually impossible to observe under real-world mixed traffic conditions [44]. Consequently, some studies have employed microsimulation to generate this hypothetical baseline [17]. Additionally, the projected rectangular area representation oversimplifies actual vehicle footprints, and

measuring dimensions for the diverse range of vehicles present in heterogeneous traffic streams requires extensive field surveys [47].

Appendix B.5. Optimization-Based Method: Data Collection Protocol

Video data are collected by monitoring the approaches of signalized intersections during both peak and off-peak times. The green interval is divided into time slices of t seconds (typically 5 or 6 s) for analysis. A critical step in the optimization method is identifying the saturated portion of the green phase [2,48]. Two approaches are employed for this purpose.

In the first approach, the first and last t -second periods from each green interval are removed from the data and the remaining flow data are then filtered using a range of mean ± 1 standard deviation to identify the saturated region [2].

The second approach uses repeated application of one-way ANOVA to test for statistical equivalence in successive pairs of green slices on flow values. A statistically equivalent p -value (>0.05) for flow values between two consecutive green slices indicates that these have entered into the saturated green region [48].

After determining the green interval, classified vehicle counts at the stop line are obtained for each time slice.

Appendix B.6. Capacity-Based Method: Data Collection Protocol

Unlike the headway ratio method, which can be applied in both field and simulation environments, the capacity-based method is exclusively applicable in simulation environments due to its requirement for homogeneous traffic streams [50,51]. The data collection procedure begins with establishing a baseline scenario where the simulation is configured with the desired intersection geometry, signal timing, and traffic demand using a traffic stream composed entirely of passenger cars, and the maximum throughput before congestion is recorded. Subsequently, test scenarios are conducted under identical conditions by replacing the traffic stream with 100% of each subject vehicle type (e.g., trucks, buses, and articulated vehicles) and recording the maximum throughput for each. Finally, PCE values are calculated by dividing the passenger car throughput by the subject vehicle throughput.

Appendix B.7. Queue-Based Method: Data Collection Protocol and Extended Formulations

Appendix B.7.1. Detailed Explanation of Queue Clearance Rate Method

The numerator incorporates a width adjustment factor as shown in Equation (A12):

$$N = \sum_{j=1}^k n_j \times \frac{w_{car}}{w_j} \times PCE_j \quad (A12)$$

where

- n_j is the number of vehicles of type j ,
- w_{car} is the width of a standard passenger car,
- w_j is the width of vehicle type j (the vehicle width ratio will account for the tendency of smaller vehicles to enter into lateral spaces between larger vehicles, thereby reducing their effective impact on queue discharge [52]),
- PCE_j is Passenger Car Equivalent for vehicle type j , and
- k is the number of vehicle categories in traffic stream.

However, these equations alone cannot directly yield PCE values, which appear as an unknown variable within the QCR formula itself. Thus, the method uses a Linear Programming (LP) technique to eliminate this circular dependency. It is assumed that when PCE values are appropriately defined, then various queue compositions will demonstrate the

same QCR values when converted to their respective PCEs. Consequently, the optimization problem minimizes the coefficient of variation in QCR across multiple observed queues, with PCE values for each vehicle category serving as decision variables. The optimization problem is formulated as follows.

Minimize $Z = CV(QCR)$ subject to constraints $PCE_j > 0$ and $PCE_{car} = 1$, where $CV(QCR)$ represents the coefficient of variation in QCR across different observed queues.

Although the QCR method contains a similar circular dependency as saturation flow-based approaches, since PCE values are embedded within the QCR formulation, it offers a practical resolution through optimization using mixed traffic observations. In contrast, saturation flow methods require car-only queue measurements that are often infeasible under heterogeneous traffic conditions.

Appendix B.7.2. Queue Composition Method

The queue-based approach evaluates the queue clearance rate (number of vehicles cleared per unit of time) for various mixtures of traffic to develop PCEs. Jithender and Mehar [83] and Jithender and Sushmitha [80] developed an alternative approach that incorporates both vehicle dimensions and spacing behaviors into the PCE formulation. In this method, PCE is defined as a function of the queue proportions, the relative vehicle widths, and the longitudinal to lateral standstill distance ratios as shown in Equation (A13):

$$PCE_i = \left(\frac{Q_i}{Q} + \frac{W_i}{W_c} \right) \times \left(\frac{D_l}{D_t} \right)_i \quad (A13)$$

where

- Q_i is the number of vehicles of type i in the queue,
- Q is the total number of queued vehicles,
- W_i is the width of vehicle type i ,
- W_c is the width of a standard car,
- D_l is the average longitudinal standstill distance, and
- D_t is the average lateral standstill distance.

The longitudinal standstill distance represents the front-to-rear gap between consecutive vehicles, while the lateral standstill distance captures the side-by-side spacing. These parameters are measured directly from field observations at the intersection approach. Standstill distances are measured during red phases when vehicles are stationary [80].

Appendix B.7.3. Data Collection Protocol

For each signal cycle, observers collect the following information.

1. The total number of vehicles in the queue when the green signal starts (excluding vehicles approaching the intersection, only vehicles stopped in the queue);
2. The mixture of vehicles in the queue by type (for example, 15 automobiles, 8 motorcycles, and 3 semi-trailer trucks);
3. The precise time interval from when the green light initiates until the final vehicle in the queue has entirely crossed the stop bar, which defines the queue clearance time [52].

Critically, the method requires saturated queue conditions where vehicles are continuously waiting at the stop line throughout multiple cycles. This ensures the clearance rate reflects the actual discharge capacity rather than gap acceptance behavior [83].

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