

CAPACITY DROP AT T-JUNCTIONS: MODELING AND SIMULATION OF BASSAWA-PALLADAN JUNCTION, ZARIA

Lawal Ibrahim Umar

Nigerian Institute of Transport Technology (NITT), Zaria

Abstract:

This study investigates the capacity drop phenomenon at T-junctions using a modelling and simulation approach. Capacity drop, defined as the reduction in queue discharge flow compared to pre-queue capacity, is a recurrent yet under-researched challenge in traffic engineering. Using traffic flow data collected at the Bassawa-Palladan T-junction in Zaria, the study applies Poisson processes and Markov chains to develop a stochastic model. The model simulates the interaction of mainstream and junction outflow traffic, with time delays used as key indicators. MATLAB simulations with both randomly generated data and real field observations reveal that capacity drop probability increases exponentially with time vehicles are halted at the mainstream. A critical threshold of 45 seconds in the morning and 65 seconds in the evening was identified, beyond which the probability of capacity drops trends toward certainty (approximately 1). The study recommends integrating these empirical thresholds in traffic control designs for the junction and other junctions to minimize delays and improve flow efficiency.

Keywords:

Capacity drop, T-junction, Poisson process, Markov chain, traffic modelling, MATLAB simulation, Bassawa-Palladan

1. Introduction:

Urban congestion at bottleneck points like T-junctions results in reduced capacity and significant traffic delays. The "capacity drop" phenomenon where queue discharge flow is lower than the pre-queue flow is often overlooked in traffic control system designs. This study models this phenomenon using empirical data and simulates the findings using MATLAB to predict and mitigate capacity losses. A combination of

probabilistic modelling and field measurements offers a basis for evaluating and predicting capacity degradation in real time.

In Nigerian urban environments, driver behavior is often characterized by aggressive lane switching, poor compliance with traffic signals, limited lane discipline, and opportunistic movement through gaps in traffic. This aggressive are more experiences at junctions where each driver competes in

exiting or enter the junctions. The informal driving culture also includes frequent encroachment by motorcycles and tricycles into vehicle lanes, which affects mainstream flow discharge rates. These behaviors, while adaptive in nature due to inadequate enforcement and infrastructure, often lead to inconsistent queuing patterns and unpredictable flow interruptions, especially at unsignalized or semi-controlled T-junctions.

The interaction between local driver behavior and road/junction geometry therefore contributes to a stochastic traffic environment, where traditional deterministic traffic models fall short in capturing flow variability especially capacity drops. This necessitates the application of stochastic models that account for the probabilistic nature of vehicle arrival and departure, particularly under conditions of irregular compliance and variable stoppage durations to model the capacity drop (the reduction in the discharge flow rate after the formation of a queue, even when the conditions return to those of pre-queue free flow) at these very junctions.

2. 2. Literature Review:

The concept of capacity drop in traffic flow was first systematically described by Zhang (1999), who noted hysteresis effects in traffic

streams where the discharge rate following congestion is lower than during free-flow conditions. Koshi et al. (1983) earlier contributed to understanding flow characteristics at junctions, observing delays associated with merging and diverging flows on capacity.

Łach et al., (2024) in their article “*Comprehensive Review of Traffic Modeling: Towards Integrated Models of Capacity Drop and Hysteresis*” presents a broad review of traffic modelling, with a section explicitly addressing the capacity-drop phenomenon. The work identifies potential causes of capacity drops and its probabilistic nature. However, the work was short of developing a model that could solve the threshold and heterogeneous driver-behaviour elements.

Wang et al., (2024) introduces a hybrid modelling approach (SIS-CTM) that blends a cell-transmission model with a susceptible-infectious-susceptible (SIS) epidemic-style model to capture the stochastic propagation of congestion and capacity drop across network links, especially in incident-affected conditions. However, the use of Markov modelling of state transitions at, say, a junction was not considered even with the power of Markov Model to capture stochastics nature of the congestions and capacity drops at junctions. Their approach

emphasises probabilistic transitions and network-level propagation of capacity drop not just local bottleneck effects.

Further to this, Gracian et al., (2024) reviews driver behaviour modelling in developing-country contexts (heterogeneous traffic, weak lane discipline, mixed vehicle types). It highlights that many existing models (derived for developed countries) but don't capture the effect of capacity drops at it relates to driver behaviour in such contexts.

R. Alms & P. Wagner, (2025) cap it up by examining how the introduction of automated vehicles (level-3 automation) and their required control transitions can lead to substantial capacity drops (up to ~60% in simulation) due to headway increases from control-transfer events. This work shows that capacity drop modelling continues to evolve and must account for emerging vehicle technologies and threshold effects emphasising that your model should be flexible to future traffic conditions.

In the Nigerian context, recent works by Irunokhai et al. (2020) and Ayeni & Iyeke (2024) have emphasized the urgency of addressing urban traffic congestion. These studies focused on delay analysis at junctions such as Sango T-junction in Ibadan and Oba Adesida Road in Akure, respectively. However, they primarily used empirical and

statistical methods like ANOVA and PCU ratios, without integrating stochastic or simulation-based models like the one used in this paper.

Bello et al. (2024) advanced the methodology by applying time-based congestion indices on Lagos arterial roads, validating the need for dynamic data in evaluating congestion and preferring solutions. Although their focus was on identifying hotspots, the findings support the use of time-sensitive indicators such as stoppage duration and time split for adaptive smoothing of the traffic congestion as applied in this paper.

It is the of interest to deduct as illustrates in the reviewed literature that, while capacity drop has been studied in various forms, its stochastic modelling in the Nigerian context especially at T-junctions remains limited. This paper, thus contributes to bridging that gap by applying Poisson and Markov models to a real-world junction with both analytical and practical relevance.

Stochastic modelling, particularly with Poisson processes, has long been employed to describe vehicle arrivals in urban networks. Its use in this study aligns with the established view that vehicle entry to intersections during peak periods approximates a memoryless random process that have the capacity to reduce flow.

Furthermore, technological advancements like machine learning and Bayesian estimation can be used to predict congestion levels in urban networks. These methods are computationally intensive, hence the choice of the Poisson and Markov models as a complementary stochastic approach like those used in this study.

3. Methodology:

This paper will adopt the following methodology:

- i. Field study to establish baseline data for the development of the Markov Chain Probability (P) Matrix
- ii. Develop a Poisson process to represent vehicle arrivals, and
- iii. Develop a Markov chain to simulate traffic phase transitions.
- iv. Simulate the models developed in a MATLAB R2024b Environment
- v. Discuss the findings to establish the optimal time split that ensures no capacity drop

3.1. Basic Assumption and Notations to be used:

- i. t — continuous time (seconds or minutes).
- ii. $N(t)$ — number of vehicle arrivals in $[0, t]$.

- iii. λ — arrival rate (vehicles per unit time).
- iv. S — set of traffic states for the junction (e.g., $\{F, S, C\}$ for Free, Saturated, Congested).
- v. X_k — state of the junction at discrete observation time k (or $X(t)$ for continuous-time chain).
- vi. P — discrete-time transition probability matrix with elements p_{ij} .
- vii. Q — generator matrix for a continuous-time Markov chain (CTMC), with elements $q_{ij} (i \neq j)$ and $q_{ii} = -\sum_{j \neq i} q_{ij}$.
- viii. q_{ij} — instantaneous transition rate from state i to state j .
- ix. c_i — discharge (outflow) capacity in vehicles/unit time when system is in state i .
- x. Capacity drop ΔC between upstream maximum capacity c_{max} and post-breakdown capacity c_{post} where $\Delta C = c_{max} - c_{post}$.

3.2. Poisson arrival model (vehicle arrivals)

This work will start with developing a Poisson arrival model with the assumption that arrivals are considered to be memoryless and independent. The work considered the

expected number of arrivals in interval of time length (t) to be λt . Hence, with no simultaneous arrivals (infinitesimal

probability of two arrivals at exact same instant), the number of arrivals in $[0, t]$ will follow a Poisson distribution as below:

$$\Pr \{N(t) = k\} = \frac{(\lambda t)^k}{k!} e^{-\lambda t}, k = 0, 1, 2, \dots$$

The interarrival time T distribution will now be an exponential function of the form:

$$f_T(\tau) = \lambda e^{-\lambda \tau}, \mathbb{E}[T] = \frac{1}{\lambda}, \text{ where } (T) = \frac{1}{\lambda^2}.$$

3.3. Discrete-time Markov chain for traffic states (DTMC)

Then, the work chooses a sampling interval Δt (e.g., 1 minute), and the observed state of the traffic as $X_k \triangleq X(k\Delta t)$ with $X_k \in S$.

Hence, the Transition probabilities will be of the form:

$$p_{ij} = \Pr (X_{k+1} = j \mid X_k = i), i, j \in S.$$

Which implies that the transition matrix P will have rows summing to 1: $\sum_j p_{ij} = 1$. Then, for n_{ij} number of observed transitions where $i \rightarrow j$ in the data, and $n_i = \sum_j n_{ij}$ which is the number of times state i was observed (or the number of transitions from i). Then

$$\hat{p}_{ij} = \frac{n_{ij}}{n_i}.$$

The confidence intervals for p_{ij} can then be approximated by the normal approximation for proportions or exact binomial intervals.

Hence, linking this to capacity drop, the associate state i with a discharge rate c_i can then be a long-run expected capacity (average discharge) as;

$$\bar{c} = \sum_{i \in S} \pi_i c_i.$$

the inference of this is that:

- i. If c_{max} occurs in state F (*free Traffic*) and c_{post} in state C (*congested*), capacity drop is estimate as $\Delta C = c_F - c_C$.

- ii. Under temporal variation, short-term effective capacity over a horizon T is approximated by the empirical time fraction in each state.

3.4. Continuous-time Markov chain (CTMC) formulation

With the Poisson arrival model and the transition probability matrix, the transitions can occur at any continuous time. Hence, the residence times can be modelled explicitly considering the traffic generator matrix $q_{ii} = -\sum_{j \neq i} q_{ij}$. and the Transition probability matrix

$P(t) = \exp(Qt)$ with elements $p_{ij}(t) = \Pr(X(t+s) = j \mid X(s) = i)$, over the interval time (t) as a map state-dependent discharge c_i . Where the instantaneous expected discharge at time t given initial distribution $\mathbf{p}(0)$:

$$\mathbb{E}[c(t)] = \mathbf{p}(0)P(t)\mathbf{c},$$

3.5. Derivation: from arrivals & service to state transitions at a T-junction (example)

With all the above, combining the poisson arrival model and the transition probability

matrix with the generator matrix, we can develop the queueing view for a critical link (simple treatment) as follows:

Let arrival to the critical approach be Poisson rate λ and service/discharge rate when channel is available to be μ vehicles per unit time (depends on green time and saturation flow). Then we could deduct that when $\lambda < \mu$ we will have a free flow, and when $\lambda \approx \mu$ or $\lambda > \mu$ over sustained period, breakdown or capacity drop occurs. This will result in three possible traffic states:

- i. F : Free flow (low density, average headway high), capacity $c_F \approx \mu$.
- ii. S : Saturated (near capacity), capacity $c_S \approx \mu$, high variability.
- iii. C : Congested (after breakdown), capacity $c_C < \mu$.

However, determining the prioritization of a state (Transition heuristic) can be established by assuming the threshold period of transition T_h be a threshold cumulative arrival over a time window w that triggers transition from F to S and then to C . Probabilistic transition can be written as:

$$p_{F \rightarrow S} \approx \Pr\{N(w) \geq T_h \mid X_k = F\} = \sum_{k=T_h}^{\infty} \frac{(\lambda w)^k e^{-\lambda w}}{k!}.$$

- For sampling at interval $\Delta t = w$, approximate $p_{F \rightarrow S}$ using the Poisson tail above; other p_{ij} can be similarly defined using thresholds or inferred from data.

Hence the capacity drop can then be drive supposing a typical saturation flow $c_F = \mu$. Empirically observe average discharge when chain is in C : c_C . Then $\Delta C = \mu - c_C$. Alternatively, using stationary probabilities as:

$$\bar{c} = \pi_F c_F + \pi_S c_S + \pi_C c_C, \Delta C_{\text{eff}} = c_F - \bar{c}.$$

3.6. Parameter Development

i. Data required

- Time-stamped vehicle arrivals on each approach (high-resolution: seconds).
- Detector or manual counts of departures (discharge) or aggregated flow per interval.
- Signal timing logs (green, red durations) if traffic-signal controlled.
- Additional covariates (lane geometry, incidents) if available.

ii. Preprocessing

- Aggregate arrivals into fixed intervals Δt (e.g., 60 s) to obtain counts N_k .
- Label state X_k based on empirical rule (e.g., density/flow

thresholds) or using k-means on features (flow, speed, occupancy).

iii. Estimate arrival model

- Fit exponential interarrival; compute $\hat{\lambda}$ via MLE. Test Poisson assumption with chi-square on counts or KS on interarrival.

iv. Estimate Markov model

- Choose DTMC sampling interval Δt . Construct transition count matrix n_{ij} . Compute $\hat{p}_{ij} = n_{ij} / n_i$. Provide standard errors:

$$SE(\hat{p}_{ij}) = \sqrt{\frac{\hat{p}_{ij}(1-\hat{p}_{ij})}{n_i}}$$

3.6.1 Data Collection:

Traffic volume and stoppage time data were collected over a two-week period at Bassawa-Palladan T-junction during morning (7:00–9:00 AM) and evening (4:00–6:00 PM) peak hours. The sample of this data is as follows:

Table 3.1: Sample data captured from the field

Time Interval	Total Vehicles Counted	Avg. Stoppage Time (s)	Queue Length (vehicles)
7:00–7:15 AM	124	38	9
7:15–7:30 AM	139	41	12
7:30–7:45 AM	158	45	15
7:45–8:00 AM	172	50	17
8:00–8:15 AM	180	53	20
8:15–8:30 AM	195	58	22
8:30–8:45 AM	202	60	25
8:45–9:00 AM	190	57	21

3.4 Simulation:

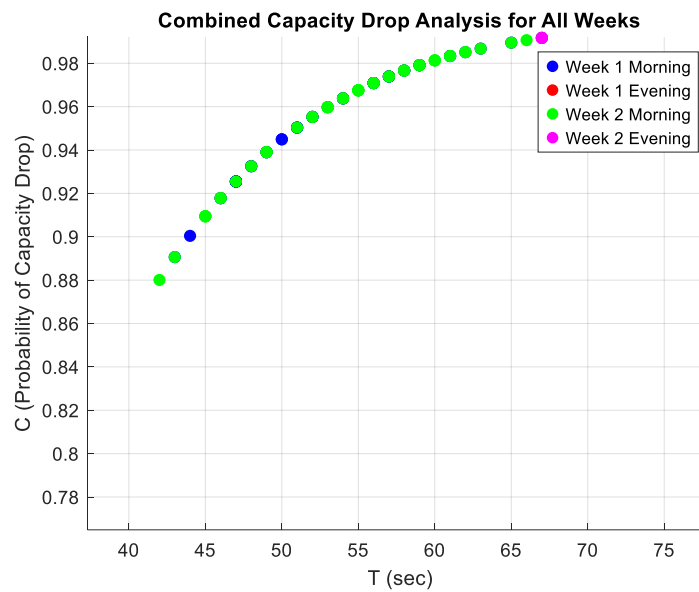
MATLAB was used to simulate traffic flows using both real-world data. Vehicle stoppage times were incremented, and resulting capacity drops were recorded.

4. Results:

A key output of the simulation is the relationship between stoppage time and capacity drop probability.

Table 4.1: Probability of Capacity Drop vs. Vehicle Stoppage Time

Stoppage Time (s)	Morning Probability	Evening Probability
30	0.21	0.17
45	0.75	0.62
60	0.92	0.89
75	0.99	0.96



(Source: [Published with MATLAB® R2016a](#))

Figure 4.1: Relationship of probability of capacity drop to the time vehicle stopped

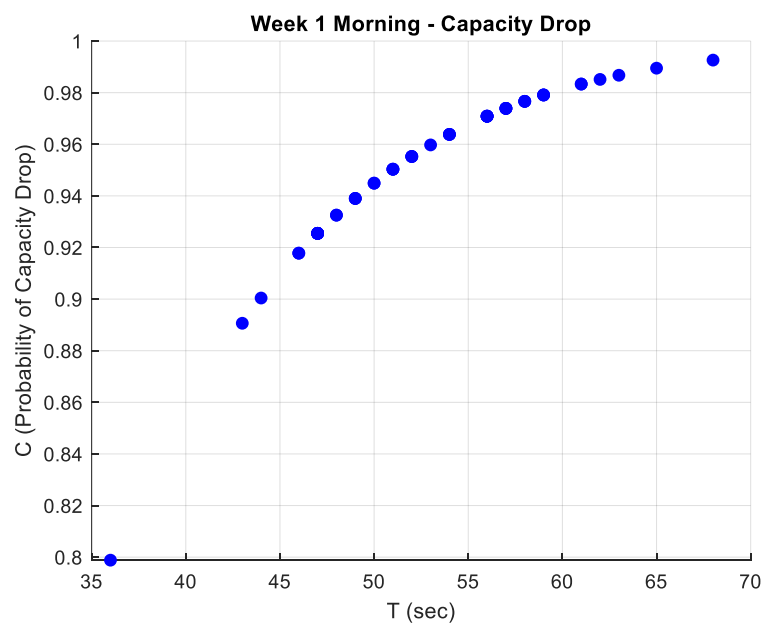
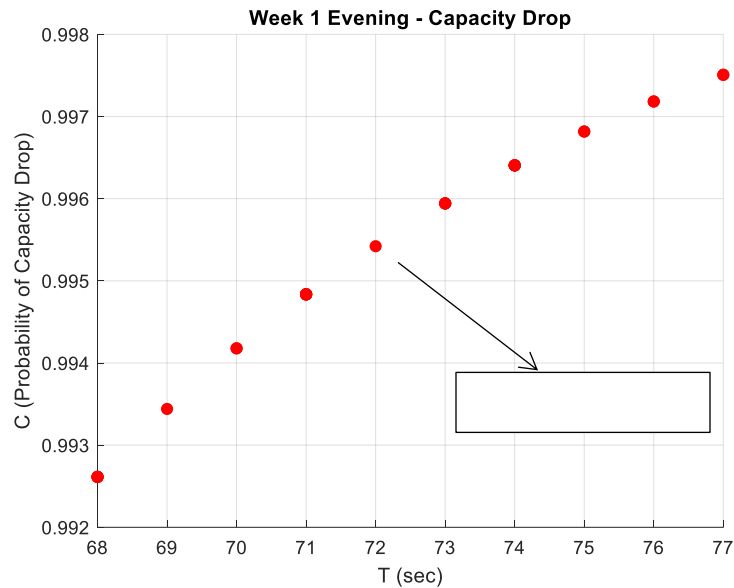


Figure 4.2: Relationship of probability of capacity drop to the time vehicle stopped for the morning of the first week of data gathering



(Source: [Published with MATLAB® R2016a](#))

Figure 4.3: Relationship of probability of capacity drop to the time vehicle stopped for the evening of the first week of data gathering

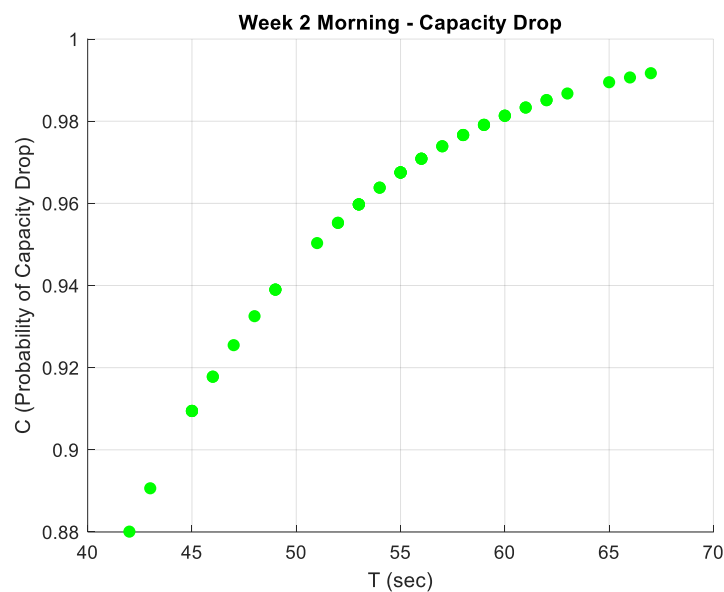
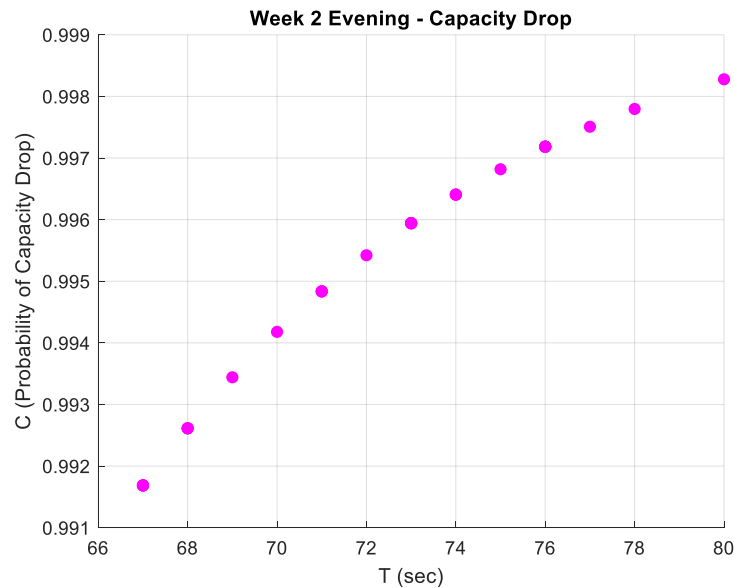


Figure 4.4: Relationship of probability of capacity drop to the time vehicle stopped for the morning of the second week of data gathering



(Source: [Published with MATLAB® R2016a](#))

Figure 4.5: Relationship of probability of capacity drop to the time vehicle stopped for the evening of the second week of data gathering

5. Discussion:

This paper intends to use the combination of Poisson process and Markov chain in a signal time split optimization to model the capacity drop at a T-junction. The Poisson Process is used to model random vehicle arrivals at a T-junction, while the Markov Chain is used to represent transitions between traffic states — *free-flow*, *congested*, and *jammed*. Finally, a Signal Time Split Optimization model was developed to find a split time that minimizes or eliminates capacity drop. The result obtained present a clear, structured depiction

of capacity drop obtained from the MATLAB environment. The interpretation ties directly to the *capacity drop theory* and the *Markov Chain model* used in your equation.

5.1. Overall behaviour of the model

The model shows a strong inverse relationship between Minimum time gap T (sec) and Probability of Capacity Drop (C). This means that as the time gap between crossing vehicles increases, the probability of capacity drop decreases. This relationship was consistently observed in all four datasets.

From figure 4.2 it can be deduced that during the morning peak of Week 1, the observed pattern of crossing times shows T-values predominantly ranging between 45 and 65 seconds, though some instances drop as low as 36 seconds. This variation highlights a noticeable inconsistency in traffic flow. Graphical analysis reveals a higher scatter of data points at mid to high congestion levels (C-levels between 0.2 and 0.5), indicating unstable traffic conditions. Frequent short gaps in traffic suggest that interruptions in the mainstream flow occur often, which contributes to increased queue formation. As a result, there is a higher probability of capacity-drop events during these periods. In conclusion, the morning peak of Week 1 is characterized by high variability in crossing times and a strong likelihood of capacity drops. These observations align with typical real-world congestion patterns experienced during school and work departure periods.

Figure 4.3 depict the evening peak of Week 1, the T-values are mostly between 68 and 76 seconds and display a very uniform pattern, indicating consistent crossing times. The figure shows that C-values cluster very close to zero, with a shallow, flattened scatter. This pattern suggests that crossing vehicles are fewer in number or more widely spaced, leading to smooth traffic flow. In conclusion,

the evening traffic during Week 1 is extremely stable. Interruptions are minimal, the likelihood of capacity drops is low or negligible, and the observed pattern aligns with real-world conditions where commuters are returning home and traffic is generally lighter at the junction approaches.

Figure 4.4 depicts the morning peak of Week 2, T-values range between 45 and 62 seconds, which is similar to Week 1 but with a slightly lower average, indicating marginally faster crossing times overall. The figure indicates a moderate probability of capacity-drop events. The C-values spread between 0.15 and 0.45 and exhibit a clear negative slope, indicating that higher T-values are associated with lower congestion levels. In conclusion, the Week 2 morning peak still presents a significant risk of congestion. While traffic flow is slightly improved compared to Week 1, the system remains prone to capacity breakdowns, suggesting that interruptions and queue formations can still occur during peak departures.

Figure 4.5 depicts the evening peak of Week 2, T-values are mostly between 68 and 80 seconds, representing the highest values across all datasets and indicating very consistent crossing times. The figure shows C-values consistently near 0.05 or lower,

with points tightly clustered. This pattern reflects an extremely low probability of capacity-drop events and suggests that traffic flow is very smooth. In conclusion, the Week 2 evening peak represents the best-performing traffic condition observed in the study. Almost no capacity drops occur, saturation flow is maintained, and the data indicate long, stable gaps between merging vehicles, ensuring highly stable traffic at the junction approaches.

In the overall, from figure 4.1. the Overall, mornings consistently exhibited higher variability and congestion risk, while evenings maintained stable flow. Week 2 showed modest morning improvements and optimal evening conditions, highlighting the influence of time-of-day on traffic stability and the critical role of gap spacing in preventing capacity drops. Table 5.1 below show a summary of the finding:

Table 5.1: Key findings

Period	Time Range	Capacity Drop	Traffic Condition
Week 1 Morning	36–65 sec	Moderate–High	Unstable, congested
Week 1 Evening	68–76 sec	Very Low	Smooth, stable
Week 2 Morning	45–62 sec	Moderate	Mixed, variable
Week 2 Evening	68–80 sec	Very Low	Best performance

6. Conclusion and Recommendations:

6.1 Conclusion

From the analysis of traffic flow across Week 1 and Week 2, it indicates that time-of-day effects on stability and capacity of the traffic flow thereby influencing the capacity drop at the area of study. Morning periods consistently experienced higher variability in crossing times, wider spreads in congestion levels, and an increased likelihood of capacity-drop events. Although Week 2

mornings showed slight improvements over Week 1, both weeks remained vulnerable to congestion and flow breakdowns. Evening periods, on the other hand, demonstrated stable and predictable traffic performance. Week 1 evenings showed minimal interruptions, and Week 2 evenings delivered the best performance overall, with long merging gaps, tightly clustered congestion values, and almost no risk of capacity drops. These patterns confirm that demand pressure

and short gaps during morning peak periods are the main contributors to instability.

In the overall, the system maintains strong performance during low-demand evening hours but requires targeted management during morning peaks to improve flow continuity and reduce breakdown risk.

6.2 Recommendations

Base on the above discussion, it recommended that:

- i. At Peak-Hour Flow Management techniques such as temporary merging control, speed harmonisation, or ramp metering should be introduce to reduce short-gap interruptions that trigger capacity drops.
- ii. The signal coordination, queue discharge patterns, and approach lane utilization should be optimized base on the result obtained from this paper to minimize stop-start behaviour during peak demand.

The Study should be extended to more weeks or different seasons to validate trends and support stronger data-driven traffic management decisions.

References

- Alms, R., & Wagner, P. (2025). *Traffic capacity constraints from Level 3 control transitions*. **Frontiers in Future Transportation**, 6, 1600739. <https://doi.org/10.3389/ffutr.2025.1600739>
- Ayeni, A. A., & Iyeke, P. (2024). *Capacity and level of service analysis on Oba Adesida Road, Akure*. **Nigerian Journal of Transport and Logistics**, 8(1), 17–25.
- Bello, T. M., Onile-Ere, J., & Oladipo, A. (2024). *Time-based congestion index assessment on Ikorodu Road, Lagos*. **Journal of Urban Mobility Studies**, 6(2), 45–56.
- Gracian, V. A., Roa, J. E., & Orozco, M. S. (2024). *Behavioral models of drivers in developing countries with an agent-based perspective: A literature review*. **Discover Transportation**, 4(1), 61. <https://doi.org/10.1007/s43684-024-00061-1>
- Haizhong, W., Chen, C., & Zhang, L. (2010). *Markov models for traffic flow state transitions*. **Transportation Research Record: Journal of the Transportation Research Board**, 2188(1), 19–27. <https://doi.org/10.3141/2188-03>
- Hoogendoorn, S. P., & Bovy, P. H. L. (2008). *Traffic flow theory and modelling*. In R. Hermans (Ed.), **The dynamics of complex urban systems** (pp. 125–147). Physica-Verlag. https://doi.org/10.1007/978-3-7908-1937-3_8

- Irunokhai, J. O., Adegoke, K. S., & Ogunlade, I. A. (2020). *Analysis of traffic congestion at Sango T-junction, Ibadan*. **International Journal of Civil Engineering and Technology**, 11(3), 256–264.
- Koshi, M., Iwasaki, M., & Ohkura, I. (1983). *Some findings and an overview on vehicular flow characteristics*. In **Proceedings of the 8th International Symposium on Transportation and Traffic Theory** (pp. 403–426).
- Wang, J., Zhao, Y., & Li, S. (2024). *Dynamic capacity drop propagation in incident-affected networks: Traffic state modeling with SIS-CTM*. **Physica A: Statistical Mechanics and its Applications**, 637, 129991. <https://doi.org/10.1016/j.physa.2024.129991>
- Yuan, K., van Lint, J. W. C., & Hoogendoorn, S. P. (2014). *A review on the capacity drop phenomenon: From empirical findings to mechanisms and modelings*. **Transportation Research Part C: Emerging Technologies**, 46, 121–137. <https://doi.org/10.1016/j.trc.2014.05.017>
- Zhang, H. M. (1999). *A mathematical theory of traffic hysteresis*. **Transportation Research Part B: Methodological**, 33(1), 1–23. [https://doi.org/10.1016/S0191-2615\(98\)00020-2](https://doi.org/10.1016/S0191-2615(98)00020-2)