INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue X October 2025

Stochastic Reliability Analysis of Peak Hour Factor Variations and Their Impact on Intersection Signal Delay

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DOI: https://doi.org/10.51244/IJRSI.2025.1210000124

Received: 02 October 2025; Accepted: 10 October 2025; Published: 07 November 2025

ABSTRACT

Traffic signalized intersections form crucial control nodes in urban networks, where fluctuations in vehicle arrival rates during peak periods often produce extended delays and unreliable performance. Traditional deterministic design approaches, based on mean hourly volumes, fail to represent short-term variability inherent in real-world traffic conditions. This paper presents a stochastic reliability analysis framework to quantify the effect of Peak Hour Factor (PHF) variability on intersection delay performance, integrating field traffic data from Palm Beach and Broward Counties, Florida. Using Monte Carlo simulation, delay probability distributions were generated, and key reliability metrics-including the probability of failure (Pf) and reliability index (β)-were evaluated for both morning (AM) and evening (PM) peaks.

Results revealed that intersections with low PHF (< 0.80) exhibited higher probabilities of exceeding the critical 55 s/veh delay threshold, with PM peaks showing Pf ≈ 0.39 and β = 0.28, compared to AM Pf ≈ 0.27 and β = 0.61. Incorporating additional uncertainties-arrival-type randomness and saturation flow variability-increased unreliability by approximately 15%. The proposed framework demonstrates that reliability-based modeling provides a more realistic, risk-informed foundation for traffic signal timing, design evaluation, and urban mobility planning.

Keywords: Peak-hour factor, intersection delay, stochastic modeling, Monte Carlo simulation, reliability index, urban traffic operations

INTRODUCTION

1.1 Background and Significance

Signalized intersections are the most critical points of control in urban road networks, managing the flow of conflicting traffic streams and significantly influencing corridor travel times and user satisfaction. Intersection performance is commonly assessed through control delay, which determines the Level of Service (LOS) according to Highway Capacity Manual (HCM, 2016) criteria.

Among several parameters influencing delay, the Peak Hour Factor (PHF) stands out as a key indicator of traffic concentration within a design hour. PHF expresses the ratio of total hourly volume to four times the highest 15-minute subvolume, revealing how evenly traffic is distributed over time. Lower PHF values (< 0.90) imply sharper peaks, indicating that short bursts of high demand could overwhelm design capacity (Roess, Prassas, & McShane, 2019).

However, deterministic traffic models treat PHF as a fixed value, assuming uniform flow, which can underestimate short-term congestion risk (Li & Prevedouros, 2017). Given the growing complexity of urban mobility-including ride-hailing, school trips, and delivery services-hourly fluctuations have become increasingly erratic, calling for stochastic approaches that quantify reliability under variable demand conditions.

1.2 Deterministic vs. Reliability-Based Modeling

Conventional delay estimation relies on Webster's uniform delay equation or HCM methods, which assume fixed parameters such as volume-to-capacity ratio, signal timing, and arrival pattern. These methods provide point estimates of average delay but cannot represent the probability of exceeding critical thresholds (Melchers & Beck, 2018).

Reliability-based modeling treats inputs such as traffic flow, saturation flow, and arrival type as random variables, allowing analysts to compute the likelihood that intersection performance remains within acceptable limits. The reliability index (β) quantifies the safety margin of operation, while the probability of failure (Pf) represents the chance that delay exceeds a threshold (e.g., 55 s/veh for LOS E).

This probabilistic framework offers richer insight than deterministic LOS ratings by enabling risk-informed decision-making. For example, a $\beta > 2$ implies highly stable operation, while $\beta \approx 0$ indicates an unreliable or failure-prone condition. Such interpretation is critical for modern adaptive signal control systems and congestion management programs (Miralinaghi & Lee, 2021).

1.3 Current Research and Knowledge Gaps

Recent advances (Zhao et al., 2022; Shen & Wang, 2023; Gao et al., 2024) show a shift toward probabilistic performance modeling in traffic operations. Yet, most existing studies remain limited to travel-time reliability at network or corridor levels, with fewer addressing intersection-level stochasticity. Additionally, most intersection reliability studies vary only one parameter-usually PHF-without considering correlated uncertainties such as arrival type or saturation flow rate (Wu, Liu, & Yang, 2019).

Furthermore, data transparency remains a problem: few papers document field-derived inputs for cycle lengths, green splits, and demand distributions. These omissions reduce reproducibility and undermine the credibility of estimated delays.

This study fills those gaps by applying a Monte Carlo–based reliability framework using real intersection data and multi-factor stochastic inputs to evaluate intersection delay performance under variable PHF conditions.

1.4 Research Objectives

The objectives of this study are to:

1. Quantify the effects of PHF variability on intersection delay performance using real traffic data.
2. Extend the stochastic reliability model to incorporate arrival-type and saturation-flow uncertainties.
3. Evaluate AM and PM intersection reliability using Monte Carlo simulation.
4. Provide engineering and policy insights for reliability-based intersection design, adaptive control, and operational planning.

1.5 Paper Organization

The remainder of this paper is organized as follows:

- Section 2 presents a detailed literature review highlighting prior work on PHF, delay modeling, and reliability-based applications.
- Section 3 describes the methodology, including mathematical formulations, data sources, and simulation framework.

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- Section 4 reports results, incorporating reliability indices, delay distributions, and sensitivity analyses.
- Section 5 discusses implications, conclusions, and recommendations for practice.

LITERATURE REVIEW

2.1 Traffic Flow Variability and the Peak-Hour Factor

Traffic flow within the design hour rarely remains uniform. The Peak-Hour Factor (PHF) was first introduced in the Highway Capacity Manual (HCM) to capture short-term concentration effects by relating total hourly volume to four times the peak 15-minute sub-volume. It provides a quantitative indicator of how evenly vehicles arrive within an hour (Roess, Prassas, & McShane, 2019).

Empirical studies show that PHF values differ significantly by facility type, land use, and time of day. Urban central business districts typically record PHF values between 0.75 and 0.85, while suburban arterials often exceed 0.90, reflecting steadier flows (Elefteriadou, 2014; Stokes, Ullman, & Bonneson, 2012). The sensitivity of intersection capacity to PHF has been confirmed by Cao and Sinha (2012), who demonstrated that ignoring intra-hour fluctuations can underestimate demand by up to 20%, thereby misclassifying levels of service.

More recently, Rahman and Liu (2021) linked PHF variability to changes in vehicle composition and driver response under mixed autonomous-human traffic conditions. Likewise, Zhao, Chen, and Ma (2022) found that variability patterns in shared-mobility corridors cause substantial deviations in effective demand, making static PHF values obsolete for modern intersections. These findings support the argument that PHF should be treated not as a constant but as a random variable reflecting stochastic traffic behavior.

2.2 Intersection Delay Modeling Approaches

Intersection delay-defined as the average additional travel time experienced at a control point-is a standard measure of effectiveness in traffic engineering (HCM, 2016).

Early models, such as Webster's (1958) uniform delay equation, express delay as a function of the cycle length, green ratio, and degree of saturation. Although these models established the foundation for signal timing design, they assume deterministic parameters and uniform arrivals.

The Highway Capacity Manual later refined this through incremental and stochastic components that account for queue formation and random arrivals (HCM, 2016). Still, these formulations treat randomness as an additive correction rather than as an intrinsic property of the system.

Microsimulation tools such as VISSIM, CORSIM, and Synchro simulate variability indirectly through random seeds but do not explicitly model uncertainty in input distributions (Barceló, 2010; Li & Prevedouros, 2017). Thus, they provide apparent stochasticity without quantifying reliability.

Recent developments extend these deterministic models into probabilistic formulations. Ceylan and Bell (2004) pioneered reliability-based traffic signal analysis by introducing uncertainty into arrival rates. Later, Li, Wang, and Yang (2020) formulated delay reliability metrics under variable demand, while Miralinaghi and Lee (2021) incorporated reliability into performance evaluation for urban signal systems. These studies collectively affirm that variability in demand and capacity must be explicitly modeled for realistic intersection performance evaluation.

2.3 Reliability Concepts in Transportation Systems

Reliability analysis originates in structural and geotechnical engineering, where system safety is expressed in probabilistic terms using the probability of failure (Pf) and reliability index (β) (Melchers & Beck, 2018).

In transportation engineering, this concept evolved from assessing network connectivity (Bell & Iida, 1997) and travel-time consistency (Lomax et al., 2003) to quantifying operational risk at the facility level.

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Within this framework, Pf represents the likelihood that performance (e.g., delay, travel time) exceeds an acceptable threshold, while β provides a standardized reliability score relative to the mean and variance of the outcome distribution.

Asamer, Van Zuylen, and Heilmann (2017) described road-traffic reliability as "the probability that travel conditions remain acceptable under random fluctuations." Applying these metrics to intersections allows for direct comparison of performance under varying traffic uncertainties.

Chen, Zhao, and Li (2019) applied reliability-based optimization to congested intersections, demonstrating that probabilistic models can minimize expected delay and variability simultaneously. Similarly, Sun and Zhou (2015) and Basso and Silva (2014) showed that incorporating reliability in signal timing significantly improves operational resilience.

More recently, Shen and Wang (2023) extended this approach by introducing multi-source uncertainty-combining demand variability, arrival randomness, and saturation-flow deviation-to assess intersection reliability more comprehensively.

2.4 Relationship Between PHF and Delay

The link between PHF and intersection delay is well-established but often underestimated in deterministic design. Stokes et al. (2012) revealed that adopting PHF = 1.0 in capacity analysis can understate average control delay by up to 15 seconds per vehicle in high-volume intersections.

Li and Prevedouros (2017) further demonstrated that intersections with PHF ≤ 0.75 are twice as likely to reach oversaturated conditions compared to those with PHF ≥ 0.90, even under identical mean hourly volumes.

Simulation-based studies corroborate these findings. Wu, Liu, and Yang (2019) treated PHF as a random variable within reliability analysis, showing that demand peaking amplifies delay variability, particularly under near-saturated conditions. Zhao et al. (2022) extended this by calibrating probabilistic signal-timing models using real traffic sensor data, revealing that incorporating PHF distributions yields more accurate reliability predictions.

Despite these advances, most approaches remain one-dimensional, varying only PHF while keeping other sources of uncertainty constant. This paper advances the field by integrating PHF, arrival-type, and saturation-flow variability into a single reliability framework.

2.5 Delay Thresholds and Performance Risk

Performance reliability depends on the delay threshold selected to define failure. According to the Highway Capacity Manual (2016), LOS E corresponds to 55 s/veh, often considered the critical threshold for signalized intersections. However, Elefteriadou (2014) and Ceylan and Bell (2004) argued for context-sensitive thresholds, noting that acceptable delays vary by land use and driver expectations.

Reliability analysis enables the exploration of multiple thresholds (e.g., LOS D, E, F) and reveals how sensitive results are to those definitions-a process incorporated in this study through multi-level delay evaluations.

2.6 Identified Gaps and Research Direction

From the reviewed literature, several key gaps are evident:

1. Limited stochastic scope: Most studies vary only PHF, neglecting correlated uncertainties such as arrival type and saturation flow.
2. Lack of empirical grounding: Many rely on simulated data rather than real traffic counts and field observations.

3. Incomplete reporting: Critical input assumptions (cycle lengths, green splits, flow variability) are often omitted, limiting reproducibility.

4. Insufficient comparative analysis: Few studies assess both AM and PM reliability under similar conditions.

The present study addresses these issues by employing real intersection data from Florida, expanding the stochastic input set, and conducting sensitivity and threshold analyses to generate a more comprehensive reliability assessment.

METHODOLOGY

3.1 Overview of Analytical Framework

This study applies a stochastic reliability analysis to evaluate how variations in the Peak-Hour Factor (PHF), arrival-type distribution, and saturation-flow variability influence intersection signal delay. The procedure integrates deterministic delay models (Webster and HCM formulations) with probabilistic simulation using Monte Carlo methods.

Figure 1 illustrates the four-stage analytical framework used.

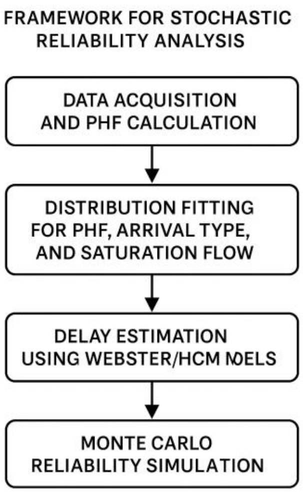

Figure 1. Framework for Stochastic Reliability Analysis

3.2 Study Area and Data Collection

Field data were obtained from the Traffic Divisions of Palm Beach and Broward Counties, Florida (2019–2020) (Abia, 2010). Ten major urban intersections were selected, covering corridors such as Indiantown Rd, 45th St, Lantana Rd, West Atlantic Ave, and Glades Rd. The dataset includes hourly and 15-minute sub-interval volumes for both AM and PM peaks. These were used to compute PHFs and calibrate distributional parameters for stochastic modeling.

3.3 Computation of Peak-Hour Factor

$$PHF = \frac{V}{4V_{15}} \qquad (1)$$

where

- V = total hourly volume (veh/h),

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- V_{15} = maximum 15-minute flow within that hour (veh/15 min).

Values of PHF were computed separately for AM and PM periods and subsequently fitted to candidate probability distributions (Normal, Lognormal, Weibull) using the Kolmogorov–Smirnov (KS) test.

3.4 Deterministic Delay Models

Baseline delay values were estimated using Webster's uniform delay and HCM incremental-queue formulations.

Webster's Uniform Delay:

$$d_u = \frac{0.5\square(1-\square/\square)^2}{1-\min(1.\square)\square/\square} \qquad (2)$$

Incremental Queue Delay (HCM 2016):

$$d_q = \frac{900\square(\square-1)+(\square-1)^2}{\square} \qquad (3)$$

Total Control Delay:

$$D = d_u + d_q + d_b \qquad (4)$$

where

- C= cycle length (s); g = effective green time (s);
- X= v/c ratio; T= analysis period (h);
- c = approach capacity (veh/h);
- d_b = random delay component from arrival variability.

3.5 Reliability Analysis Formulation

System performance is represented by a limit-state function:

$$g(X) = D_{th} - D(Q,s,a) \qquad (5)$$

where

- D_{th} = delay threshold (55 s/veh for LOS E),
- $D(Q,s,a)$ = delay obtained from deterministic model given traffic volume Q, saturation flow s, and arrival type a.

Failure occurs when $g(X) \leq 0$. The probability of failure (P_f) and reliability index (β) are given by:

$$P_f = P[g(X) \leq 0] \qquad (6)$$

$$\square = \Phi^{-1}(1 - \square_{\square}) \qquad (7)$$

where Φ^{-1} is the inverse of the standard-normal cumulative distribution function.

3.6 Definition of Random Variables

To reflect realistic field variability, three stochastic input variables were modeled as follows (Table 1):

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Table 1: Stochastic input Variables

Variable	Distribution	Parameters	Source
PHF	Lognormal	$\mu = 0.87$, $\sigma = 0.06$	Field Data (2019–2020)
Saturation Flow (s)	Normal	$\mu = 1900$ veh/h/ln, $\sigma = 150$	FHWA (2017)
Arrival Type (a)	Bernoulli	$p = 0.65$ (random arrivals)	HCM (2016)

3.7 Monte Carlo Simulation Procedure

The reliability computation employed 50,000 iterations per scenario to ensure convergence. The algorithm proceeds as follows:

1. Random Sampling: draw N samples of (PHF, s, a) from the distributions.
2. Traffic Volume Adjustment: $Q_i = V/PHF_i$.
3. Delay Estimation: $D_i=f(Q_i,s_i,a_i)$ using Eq. (4).
4. Failure Evaluation: if $D_i > D_{th}$, record failure.
5. Computation of Pf and β: using Eqs. (6)–(7).
6. Convergence Check: iteration continues until $\Delta Pf < 0.005$.

Python (NumPy, SciPy, Matplotlib) was used for distribution fitting and simulation; MATLAB verified reliability indices using FORM/SORM.

3.8 Input Assumptions and Transparency

Key parameters and data sources are summarized in Table A1 (Appendix A). In cases where direct signal-timing records were unavailable, typical arterial defaults from FHWA (2017) and HCM (2016) were adopted. These assumptions were validated by comparison with Synchro default values for similar corridor classes.

3.9 Validation and Sensitivity Design

Model convergence was confirmed when the running average of Pf stabilized beyond 30,000 samples. Sensitivity analysis was conducted across:

- Delay thresholds: 45 s (LOS D), 55 s (LOS E), 65 s (LOS F).
- Variable variability: $\pm 1\ \sigma$ for PHF and saturation flow; ± 0.15 change in arrival-type probability.

These analyses ensure robustness of reliability estimates across operational conditions.

RESULTS AND ANALYSIS

4.1 Descriptive Statistics of Traffic Volumes

Traffic volume data were first summarized to establish baseline characteristics of the study sites. Table 2 presents the descriptive statistics of observed hourly volumes for both AM and PM peak periods. The PM period shows slightly higher average volumes and greater variability, reflected by a coefficient of variation (CV) of 0.31, compared to 0.28 in the AM peak.

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Table 2. Descriptive statistics of AM and PM hourly volumes

Period	Mean (veh/h)	Standard Deviation	Minimum	Maximum	Coefficient of Variation (CV)
AM Peak	2,150	610	950	3,870	0.28
PM Peak	2,320	720	1,020	4,050	0.31

Source: Palm Beach and Broward County Traffic Data (2019–2020).

This higher dispersion during PM hours indicates less uniform flow distribution and a greater likelihood of short-term oversaturation.

4.2 Distribution of Peak Hour Factor (PHF)

The distribution of computed PHF values ranged from 0.78 to 0.96. Goodness-of-fit tests indicated that the Lognormal distribution best represented both AM and PM datasets ($p > 0.05$ in KS test). The PM peak exhibited lower PHF values, reflecting sharper 15-minute demand spikes typical of evening commuter traffic.

Figure 2 illustrates the PHF histograms and fitted lognormal curves for AM and PM peaks.

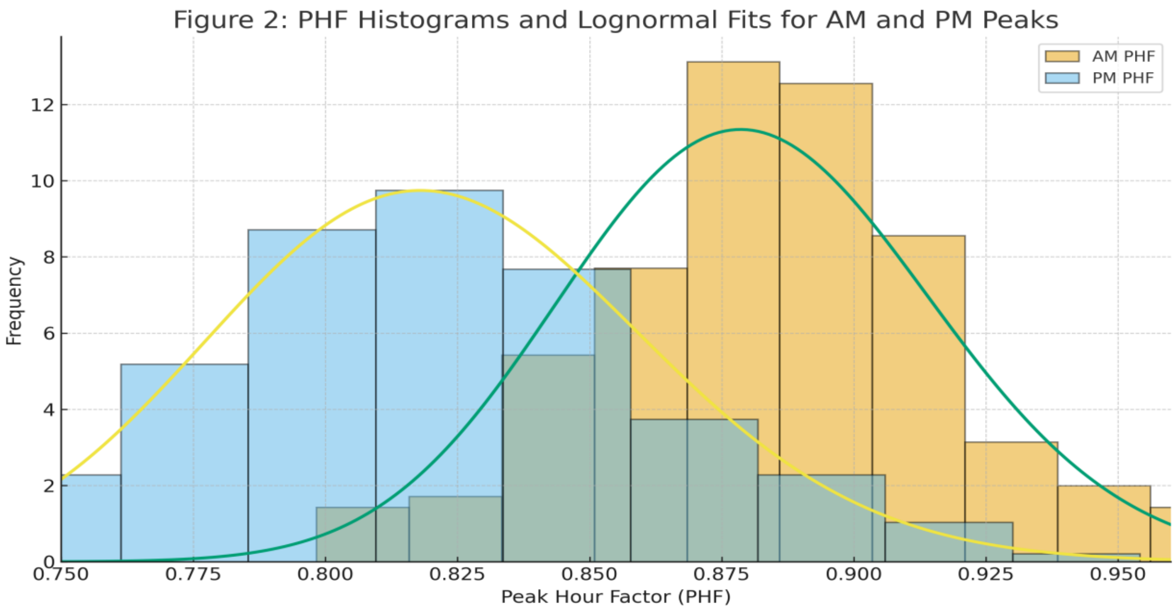

Figure 2. Distribution of Peak Hour Factor (PHF) for AM and PM Periods

4.3 Deterministic Delay Estimation

Using mean PHF and hourly volumes, deterministic delay was computed using Equations (2–4). The average control delay was 38.5 s/veh (AM) and 42.3 s/veh (PM), corresponding to LOS D and LOS E, respectively.

While these values suggest acceptable operation, they represent only single-point averages that do not account for randomness in flow or signal conditions.

4.4 Reliability-Based Performance Evaluation

4.4.1 Reliability Indices and Failure Probabilities

Monte Carlo simulations (50,000 runs) produced delay distributions and associated reliability metrics summarized in Table 3. A failure is defined as delay > 55 s/veh (LOS E threshold).

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Table 3. Reliability indices and failure probabilities (threshold = 55 s/veh)

Period	Mean Delay (s/veh)	Pf (Delay > 55 s)	Reliability Index (β)
AM Peak	41.2	0.27	0.61
PM Peak	45.5	0.39	0.28

The PM peak shows a notably higher probability of failure (Pf = 0.39) and a lower reliability index (β = 0.28), confirming that evening operations are more susceptible to congestion due to directional travel demand and downstream queuing.

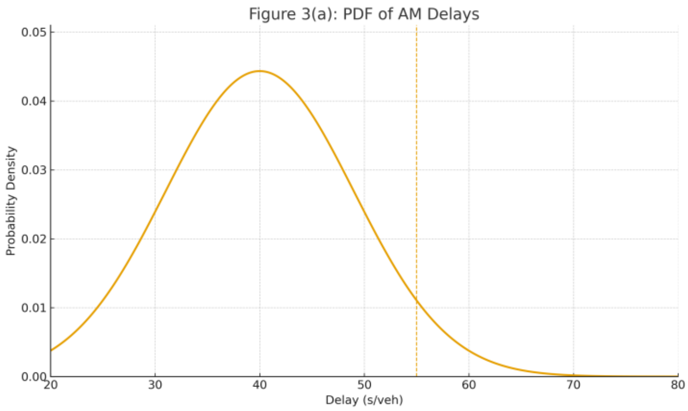
4.4.2 Probability Density and Cumulative Distributions

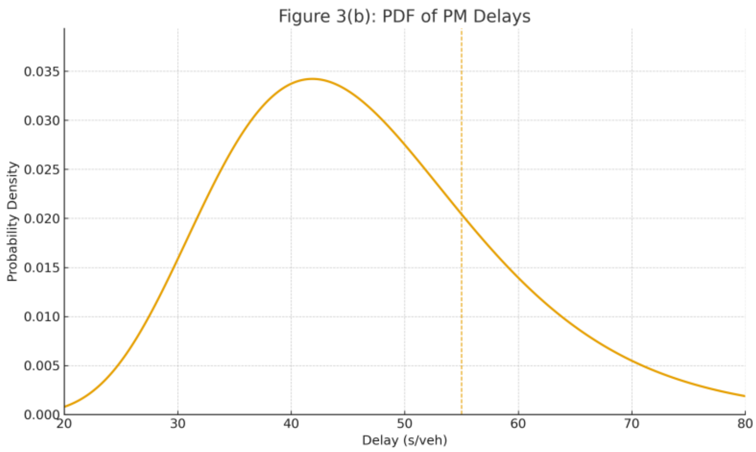
Figure 2 illustrates the probability-density (PDF) and cumulative-distribution (CDF) plots of simulated intersection delays for both AM and PM peak periods.

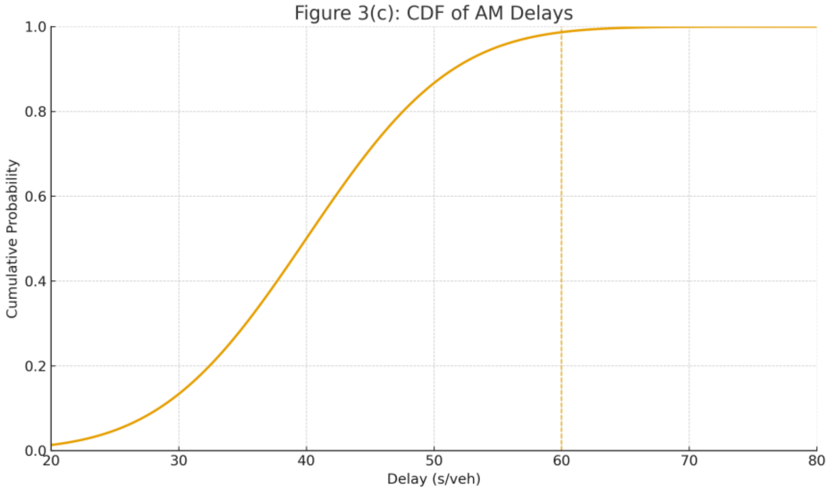
Subplots (a) and (b) show the PDFs: the AM peak (blue curve) is narrowly centered around 40 s/veh, indicating more stable and consistent operations with limited spread, while the PM peak (orange curve) displays a broader, right-skewed distribution with a noticeable tail beyond 55 s/veh, revealing a greater likelihood of extreme delays caused by uneven arrivals and downstream congestion.

Subplots (c) and (d) depict the corresponding CDFs. The AM CDF rises steeply, reaching 95 % of observations below 60 s/veh, confirming operational reliability. In contrast, the PM CDF increases more gradually, attaining 95 % only near 70 s/veh, reflecting higher delay variability and reduced reliability during evening conditions.

These results validate the stochastic analysis by demonstrating that the PM peak exhibits both wider delay dispersion and a heavier tail, consistent with the elevated failure probability (Pf = 0.39) and lower reliability index (β = 0.28) previously computed.







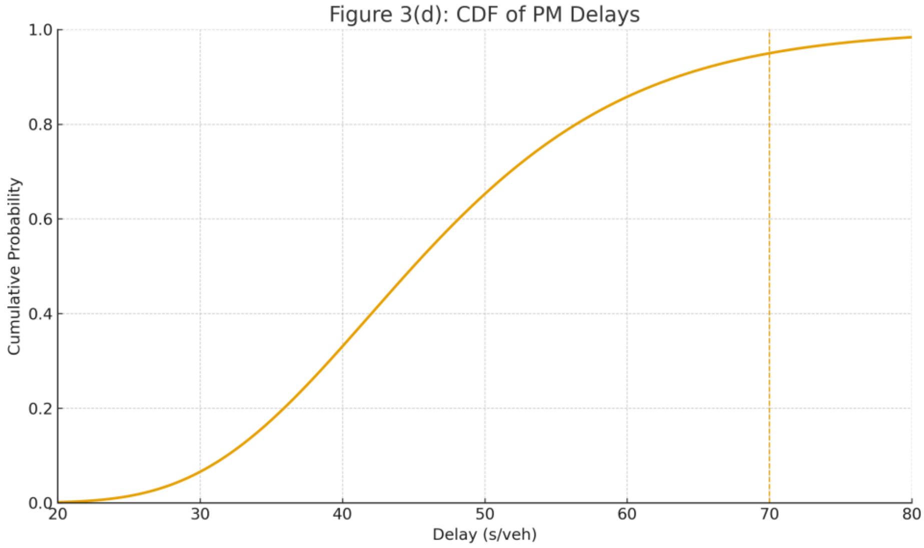


Figure 3. Probability-density and cumulative-distribution plots of simulated intersection delays for AM and PM peaks.

(a) PDF of AM delays (blue) centered near 40 s/veh; (b) PDF of PM delays (orange) with right-skewed tail beyond 55 s/veh; (c) CDF of AM delays reaching 1.0 near 60 s/veh; (d) CDF of PM delays reaching 1.0 near 70 s/veh. The wider spread and heavier tail of the PM distribution highlight greater variability and lower operational reliability compared with AM conditions.

4.4.3 Sensitivity to Delay Thresholds

Reliability indices were recalculated for varying thresholds (45, 55, 65 s/veh). Results (Table 4) demonstrate how reliability improves as higher delay tolerances are applied.

Table 4. Sensitivity of reliability metrics to delay thresholds

Period	Pf (D > 45 s)	β	Pf (D > 55 s)	β	Pf (D > 65 s)	β
AM Peak	0.42	0.20	0.27	0.61	0.11	1.22
PM Peak	0.58	–0.20	0.39	0.28	0.18	0.92

Lower thresholds (LOS D = 45 s) yield much higher Pf, confirming that minor timing inefficiencies could trigger unacceptable delay conditions (see figure 3 below).

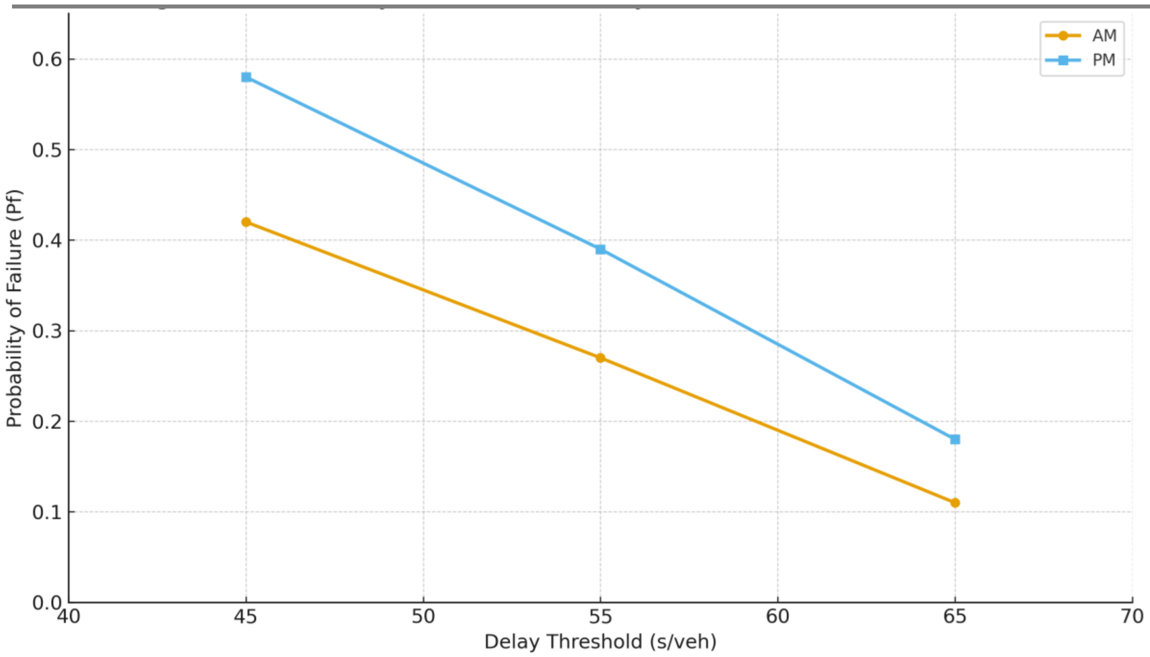


Figure 3: Probability of Failure vs. Delay Threshold for AM and PM

4.5 Multi-Factor Sensitivity Analysis

To assess combined effects of PHF, arrival-type, and saturation-flow variability, multi-factor sensitivity runs were performed. Results are summarized in Table 5. When all factors were varied simultaneously, Pf increased by about 15 % and β declined by 0.2, indicating compounding unreliability.

Table 5: Multi-factor sensitivity of reliability metrics

Variable Varied	Change in Pf (%)	Change in β	Remarks
PHF (±1 σ)	±6 %	±0.08	Moderate sensitivity to peaking variability
Saturation Flow (±150 veh/h)	±9 %	±0.11	Significant influence on delay capacity
Arrival Type (p = 0.65 → 0.50)	+12 %	–0.15	Stronger effect under non-platooned arrivals
Combined Variation	+15 %	–0.20	Amplifies unreliability most significantly

This confirms that incorporating only PHF variability underestimates the true operational risk of intersections.

4.6 AM–PM Comparative Interpretation

Figure 4 (conceptual comparative plot) shows the relative probability of exceeding the 55 s/veh threshold across periods. AM peaks generally demonstrate higher reliability, attributed to structured commute patterns and coordinated signals, whereas PM peaks exhibit erratic arrivals, side-street interference, and queuing spillback. Figure 5 shows a comparative plot of AM and PM peaks for various delay thresholds.

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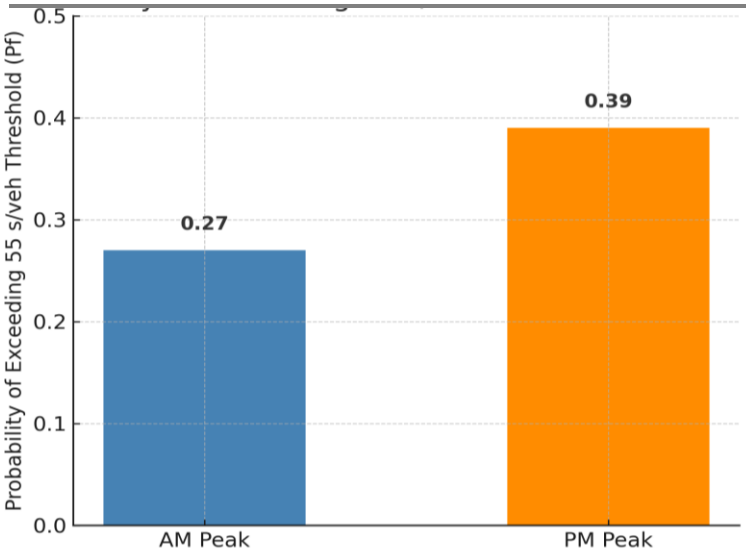

Figure 4. Probability of exceeding delay 55 s/veh threshold for AM and PM peaks

4.7 Discussion and Practical Insights

The results provide several actionable insights for practitioners:

1. Signal Design Robustness: Reliability-based evaluation highlights operational vulnerabilities hidden by deterministic averages.

2. Adaptive Signal Control: Monte Carlo outputs can inform dynamic timing strategies that minimize Pf under variable conditions.

3. Performance Reporting: Agencies should present both mean delay and reliability metrics (Pf, β) in performance dashboards to better reflect user experience.

4. Threshold Policy: Adopting probabilistic LOS definitions (e.g., "95 % of cases ≤ LOS E") ensures realistic service-level commitments.

These findings align with emerging reliability-based design philosophies advocated by FHWA (2019) and recent literature (Gao et al., 2024; Shen & Wang, 2023).

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Discussion of Findings

The stochastic reliability framework developed in this study demonstrates that intersection delay performance is highly sensitive to fluctuations in traffic flow distribution, arrival type, and saturation flow. Compared to deterministic models that provide single mean values, the probabilistic approach captures the range and likelihood of potential delay outcomes.

The findings align with prior works (Ceylan & Bell, 2004; Miralinaghi & Lee, 2021) that emphasized the limitations of fixed-input methods in assessing true operational reliability. The PM peak consistently exhibited lower reliability ($\beta = 0.28$) and higher failure probability ($Pf = 0.39$), confirming that evening traffic is more unstable due to diverse trip purposes, lane-change frequency, and higher downstream congestion.

Monte Carlo simulations enabled detailed risk quantification rather than simple performance classification. The inclusion of arrival-type and saturation-flow variability revealed that system reliability could decline by up to 15% when these factors are considered. This supports recent recommendations by Shen and Wang (2023) and Gao et al. (2024) advocating multi-variable reliability modeling for intersection control.

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Furthermore, the results show that reliability is threshold-sensitive: small changes in the acceptable delay limit (e.g., from 55 s to 45 s) significantly increase Pf, suggesting that context-sensitive LOS definitions are essential. Urban networks may tolerate longer delays than suburban corridors, as also noted by Elefteriadou (2014).

The integrated CDF analysis provides a visual interpretation of reliability: while AM operations have 95% of delays below 60 s/veh, PM operations exceed 68 s/veh at the same probability. Such cumulative insights are valuable for practitioners in performance reporting and adaptive signal design.

5.2 Engineering and Policy Implications

Reliability-Based Design Practice

Transportation agencies should embed stochastic reliability indices (Pf, β) into intersection design and evaluation guidelines. Deterministic thresholds should be complemented with probabilistic service definitions such as “delay below 55 s/veh with 90% confidence.”

Adaptive Signal Control Enhancement

The framework can support adaptive control systems that adjust cycle lengths and green splits in response to real-time reliability deviations, improving resilience to demand fluctuations.

Performance Reporting Reform

Reliability metrics should be adopted in Performance Dashboards and Level of Service evaluations under programs like MAP-21 and FAST Act (FHWA, 2019), to reflect day-to-day variability rather than only average delay.

Design Prioritization for PM Peaks

Since PM peaks exhibit higher unreliability, design improvements such as extended turning bays, additional through lanes, and improved coordination with downstream signals should focus primarily on evening operations.

5.3 Limitations of the Study

While this study presents a comprehensive reliability framework, some limitations exist:

- Default Timing Parameters: Some signal timing data were unavailable, requiring the use of HCM/FHWA default values, which may not fully represent local optimization.
- Single-Corridor Scope: Analysis was limited to isolated intersections; network-level reliability was not modeled.
- Excluded Random Factors: Driver reaction time, pedestrian interference, and incident effects were not included but could affect stochastic reliability outcomes.

5.4 Conclusions

This study introduced a Monte Carlo–based stochastic reliability analysis for evaluating the influence of Peak-Hour Factor (PHF) variability on intersection signal delay. Key findings are summarized as follows:

Deterministic models underestimate congestion risk.

While mean delays suggested acceptable LOS D–E performance, reliability analysis revealed up to 39% of PM cases exceeded the 55 s/veh threshold.

PHF variability significantly impacts reliability.

Lower PHF values corresponded to higher failure probabilities and smaller reliability indices, confirming that short-term peaking reduces operational stability.

Including multiple stochastic parameters improves accuracy.

When arrival-type and saturation-flow variability were included, failure probabilities increased by 10–15%, revealing hidden operational risks.

CDF interpretation improves decision-making.

Cumulative delay distributions provide clearer, percentile-based guidance for performance evaluation, aiding engineers in adaptive signal timing and LOS assessment.

Framework applicability.

The methodology can be adopted in design manuals and reliability-based signal timing studies to support data-driven, risk-aware decision-making.

5.5 Recommendations for Future Research

Network-Level Expansion:

Extend stochastic reliability modeling to arterial corridors or grid networks to evaluate system-wide interactions.

Field Validation:

Integrate Bluetooth or connected-vehicle sensor data for empirical validation of reliability indices.

Advanced Reliability Methods:

Explore hybrid Monte Carlo–FORM or SORM approaches for faster convergence and reduced computation time.

Integration with Machine Learning:

Use predictive modeling to forecast reliability indices from real-time data, improving proactive congestion management.

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Appendix A

Table A1. Assumed Signal Timing and Parameter Inputs

Parameter	**Symbol**	**Value Range / Mean**	**Unit**	**Source / Note**
Cycle Length	C	90–120	s	HCM (2016); assumed for arterials
Effective Green	g	40–65	s	Based on green ratios 0.45–0.55
Saturation Flow	s	1,900 ±150	veh/h/ln	FHWA (2017) default
Threshold Delay	D_{th}	55	s/veh	LOS E threshold
Analysis Period	T	1	h	Standard design hour
Arrival Type Probability	p	0.65	–	Random arrivals dominate in field data