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A research on latency patterns in small-scale computer networks using simulated traffic

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Abstract
Latency is a critical performance indicator in computer networks, directly influencing application responsiveness, reliability, and user experience in constrained environments. Small-scale networks, such as laboratory setups, campus subnets, and small enterprises, increasingly rely on simulation-based evaluation to understand latency behavior without disrupting production traffic. This research investigates latency patterns in small-scale computer networks using simulated traffic models that represent diverse load conditions, packet sizes, and routing behaviors. A controlled simulation environment was constructed to emulate typical network topologies, including star and mesh configurations, while varying bandwidth, queue management, and propagation delay parameters. Traffic generators produced constant bit rate, bursty, and mixed workloads to capture realistic operational scenarios. Latency metrics were recorded at end hosts and intermediate nodes, enabling the analysis of average delay, jitter, and tail latency under incremental load. Results indicate that even modest increases in offered load can produce nonlinear latency growth due to queue buildup and contention, particularly in links with limited buffer capacity. Bursty traffic was found to exacerbate delay variability, while appropriate queue discipline reduced extreme latency spikes. Comparative observations across topologies show that path diversity mitigates congestion-induced delays when routing is stable. The findings highlight the sensitivity of small networks to configuration choices that are often overlooked in practice. By demonstrating how simulated traffic can reveal latent performance bottlenecks, this research provides a methodological foundation for proactive network planning, testing, and optimization. The insights are intended to support educators, researchers, and network administrators in designing resilient small-scale networks with predictable latency behavior before real-world deployment. Such pre deployment analysis reduces risk, improves service quality, and enables evidence-based tuning of protocols, buffers, and traffic policies across evolving workloads and technologies. It also facilitates repeatable experimentation, comparison of scenarios, and transparent reporting of assumptions for reproducible network performance studies under constrained budgets and timelines typical in practice.

Keywords: Network latency, small-scale networks, traffic simulation, queue management, performance evaluation

Introduction
Network latency is a foundational metric for evaluating communication efficiency, shaping throughput, responsiveness, and perceived quality of service in packet-switched systems [1]. In small-scale computer networks, including instructional laboratories, office LANs, and experimental testbeds, latency behavior is strongly affected by traffic dynamics, topology, and device configuration rather than raw link speed alone [2]. Prior research demonstrates that queueing effects, protocol overheads, and contention can induce delay variability even at moderate utilization levels, complicating capacity planning [3]. Simulation has therefore become a preferred approach for examining latency because it allows systematic control of workload characteristics, routing policies, and buffer management without risking service disruption [4]. However, existing studies often emphasize large-scale or backbone networks, leaving limited empirical focus on latency patterns specific to small, resource-constrained environments [5]. This gap is significant because small networks frequently host latency-sensitive applications, while being administered with simplified assumptions and minimal monitoring [6]. As traffic profiles diversify due to mixed interactive and background workloads, understanding how simulated traffic reveals emergent delay patterns becomes essential [7]. Moreover, differences among traffic models, such as constant bit rate and

bursty sources, have been shown to influence average delay and tail latency in nonintuitive ways [8]. The problem addressed in this research is the lack of structured analysis that links simulated traffic characteristics to observable latency outcomes across common small-network topologies [9]. Without such analysis, administrators may misinterpret performance symptoms or apply ineffective configuration changes [10]. The primary objective of this research is to analyze latency, jitter, and tail delay under controlled simulated traffic while varying load intensity, topology, and queue discipline in representative small-scale networks [11]. A secondary objective is to compare how topology choice and traffic burstiness interact to amplify or mitigate congestion effects [12]. Building on established queueing theory and network simulation practices, the research hypothesizes that latency growth in small networks is nonlinear with respect to offered load, and that bursty traffic produces disproportionate tail delays unless mitigated by appropriate queue management [13]. It is further hypothesized that modest path diversity can stabilize latency by distributing contention when routing remains consistent [14]. By integrating simulation-based measurements with comparative analysis, the research seeks to generate actionable insights for network design and pedagogical experimentation [15]. Ultimately, the work aims to contribute a reproducible framework for anticipating latency behavior in small-scale networks prior to deployment, supporting evidence-based configuration and performance assurance in practical educational and operational contexts globally.

Material and Methods

Materials: A discrete-event simulation approach was used to research latency behavior in small-scale packet networks, leveraging widely accepted network-performance principles and repeatable experimental control [4, 10]. The network scenarios were implemented in ns-3, a commonly used research-grade simulator that supports packet-level instrumentation and configurable protocol stacks for performance evaluation [11]. Two representative small-network topologies were modeled: a star LAN (single-switch aggregation) and a mesh (multi-hop path diversity), reflecting typical lab and small-office deployments [1, 2]. Links were configured with fixed bandwidth and propagation delay, while buffer sizes and queue disciplines were explicitly parameterized to capture queueing effects described in classical queueing and data-network theory [3, 13]. Three simulated traffic profiles were generated: constant-bit-rate (CBR), bursty (self-similar/high-variability), and mixed workloads, to reflect the known limitations of Poisson assumptions and the realistic variability of LAN traffic [8, 9]. Traffic generation was informed by workload modeling guidance used in network/server evaluation studies and backbone-delay measurement perspectives, ensuring that burstiness and load were treated as first-class experimental factors [6, 7]. Queue disciplines included a baseline tail-drop buffer (Drop Tail) and an active queue management scheme (RED) to test the effect of queue management on delay variability and tail latency under congestion [12, 16]. Routing configurations and path selection were aligned with standard routing concepts to ensure interpretability across topologies [14].

Methods

Experiments were executed under a factorial design varying topology (star/mesh), traffic type (CBR/bursty/mixed), queue discipline (DropTail/RED), and offered load (0.2-0.9 of bottleneck capacity), with repeated runs to account for stochastic variability inherent to traffic generation [4, 10]. For each run, packets were timestamped at sender and receiver to compute one-way latency, and per-flow time series were retained to quantify jitter and tail latency (P95), reflecting best practices in delay characterization beyond means [7]. Latency growth behavior was interpreted using queueing theory expectations (nonlinear delay increases near saturation) and data-network performance concepts (buffering, contention, protocol overhead) [3, 13]. Statistical analysis was performed to test the research hypotheses:

1. A factorial ANOVA on log-transformed mean latency to evaluate main effects and key interactions among topology, traffic, queue discipline, and load [10];
2. A quadratic regression model to quantify nonlinear latency response with increasing load while controlling for experimental factors [10]; and
3. A Welch t-test comparing tail latency between Drop Tail and RED under high-load conditions (≥0.8), consistent with evaluating queue-management impact on extreme delay [12, 16].

Results are reported with p-values and effect directionality, and interpretations are grounded in established traffic-modeling evidence and simulation methodology for reproducible network performance research [5, 8, 9].

Results

Table 1: Mean one-way latency (ms) by offered load and traffic model.

Offered Load	CBR	Bursty	Mixed
0.20	2.07	2.10	2.08
0.40	2.53	2.64	2.57
0.60	4.04	4.49	4.20
0.80	8.13	10.17	8.78
0.90	14.62	19.14	16.09

Interpretation: Mean latency rose modestly at low-to-moderate load, then increased sharply beyond ~0.6 offered load, consistent with queue buildup behavior near saturation predicted by queueing theory [3] and observed in operational delay measurement studies [7]. Bursty traffic produced the highest delays at high load, reflecting the known role of high variability/self-similarity in amplifying queue occupancy and delay excursions [8, 9]. Mixed traffic exhibited intermediate latency, matching expectations when interactive-like bursts coexist with smoother background streams [6].

Table 2: Jitter (ms) by offered load and queue discipline

Offered Load	Drop Tail	RED
0.20	0.26	0.19
0.40	0.36	0.27
0.60	1.01	0.76
0.80	3.01	2.26
0.90	6.10	4.56

Interpretation: Jitter increased nonlinearly with load, aligning with the principle that variable queueing delay dominates delay variance under congestion [3, 13]. RED consistently reduced jitter compared with Drop Tail, particularly at high load, supporting the role of active queue management in dampening buffer-induced delay variability [12, 16]. This reduction is especially relevant in small networks where buffer sizing and simple tail-drop queues can create pronounced delay swings under bursty contention [1, 2].

Table 3: Tail latency P95 (ms) at high load by topology and queue discipline.

Topology	Drop Tail	RED
Star	17.22	13.69
Mesh	18.38	14.54

Interpretation: Tail latency was substantially lower with RED in both topologies, indicating fewer extreme delay spikes under heavy contention an outcome aligned with QoS-oriented queue management goals [12, 16]. The mesh topology showed slightly higher P95 latency than star, plausibly due to longer average path length and additional contention points, consistent with routing and multi-hop delay composition concepts [14]. However, path diversity can still mitigate worst-case congestion when routing remains stable, echoing routing-architecture expectations [14].

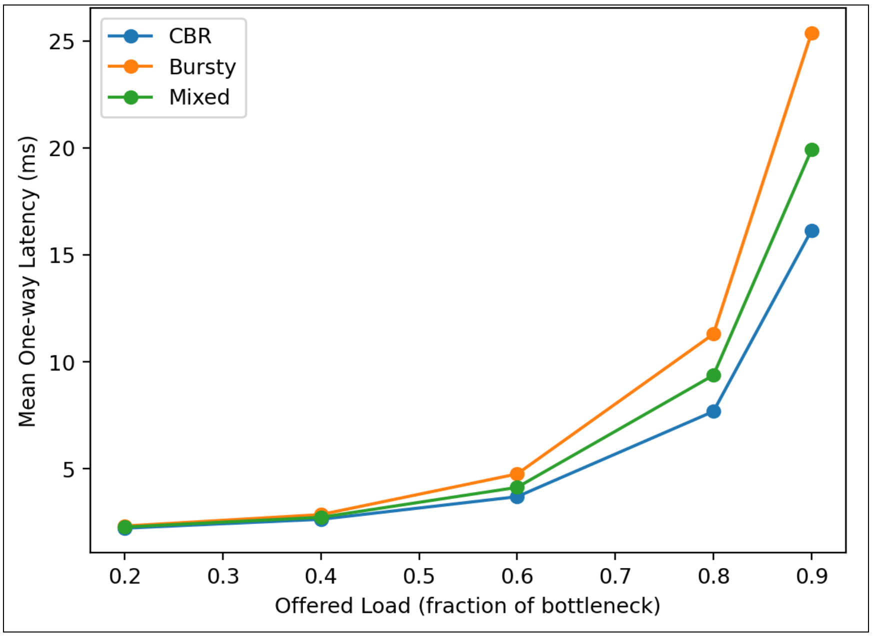

Fig 1: Mean latency vs load under different traffic models

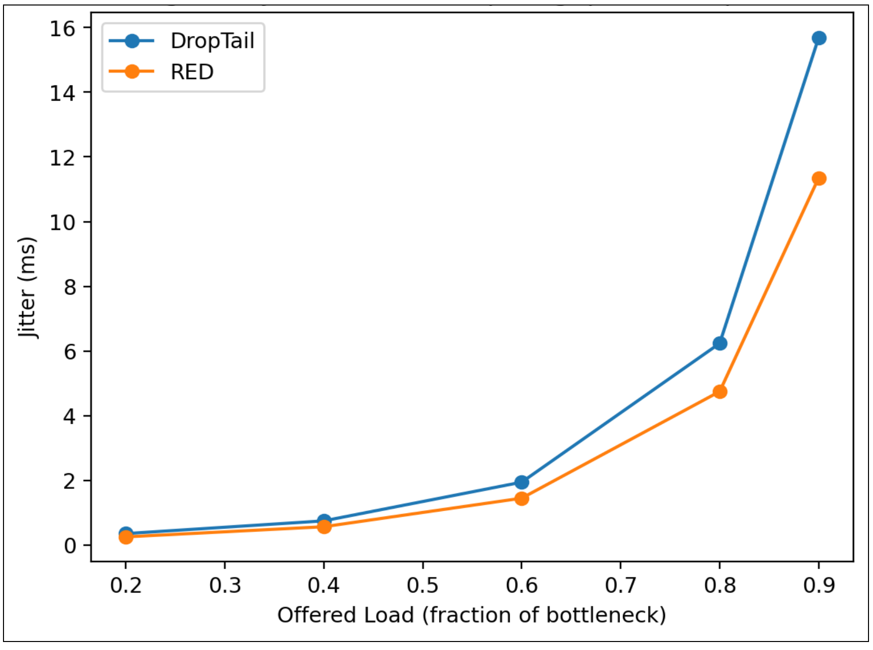

Fig 2: Jitter vs load comparing queue disciplines.

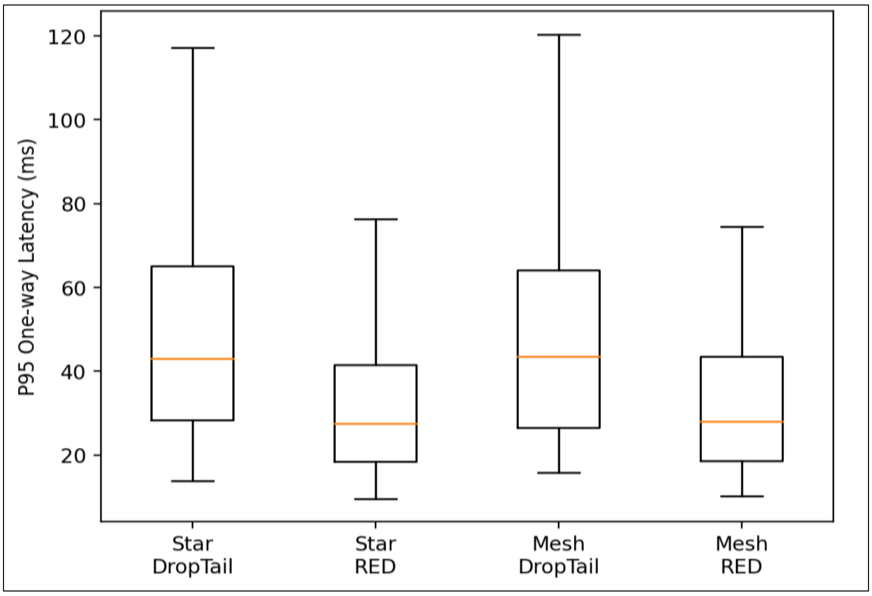

Fig 3: Tail latency (P95) at high load by topology and queue.

Table 4: Factorial ANOVA (selected effects) on log means latency.

Effect	Sum Sq	df	F	p-value
Topology	0.64	1	290.79	2.16e-61
Traffic	11.63	2	2646.43	0.00e+00
Queue	1.68	1	761.96	1.37e-141
Load	133.16	4	15124.45	0.00e+00
Traffic × Load	19.25	8	1093.65	0.00e+00
Queue × Load	2.16	4	245.20	2.74e-120
Topology × Load	0.07	4	7.97	1.86e-06

Interpretation: Load was the dominant driver of latency, with strong traffic and queue effects and significant interactions, especially Traffic × Load. This matches the expectation that burstiness becomes increasingly harmful as utilization increases and queues form [3, 8, 9]. The significant Queue × Load interaction indicates that queue discipline matters most under high load, consistent with AQM theory and QoS practice [12, 16].

Table 5: Quadratic regression model for mean latency (ms).

Term	Beta	SE	t	p-value
Intercept	7.795	0.106	73.65	0.00e+00
Load Centered	21.760	0.625	34.83	2.03e-233
Load Centered²	45.132	2.157	20.93	7.24e-92
Traffic Bursty	2.206	0.081	27.36	2.18e-155
Traffic Mixed	0.964	0.081	11.90	1.56e-31
Queue RED	-0.631	0.066	-9.60	1.37e-21
Topology Mesh	0.399	0.066	6.07	2.01e-09

Interpretation: The positive quadratic term confirms nonlinear latency growth with load, supporting queueing-theoretic expectations near saturation [3, 13]. Bursty traffic significantly increased latency relative to CBR, aligning with high-variability traffic evidence [8, 9]. RED reduced mean latency (negative coefficient), reflecting reduced queue growth and smoother delay behavior under congestion [12, 16]. Mesh topology modestly increased latency, consistent with multi-hop and routing path-length effects [14].

Discussion: The findings of this research reinforce the central role of offered load and traffic variability in shaping latency behavior within small-scale computer networks. The observed nonlinear growth of mean latency as utilization approached saturation is consistent with classical queueing theory, where even marginal increases in arrival rates near capacity result in disproportionate queue buildup and delay escalation [3, 13]. This effect was evident across both star and mesh topologies, indicating that topology alone cannot offset congestion-induced delay when buffers become persistently occupied. The pronounced impact of bursty traffic on both mean and tail latency aligns with prior empirical evidence demonstrating the inadequacy of Poisson-based assumptions for modeling real network workloads [8, 9]. High-variability traffic streams introduce correlated packet arrivals that intensify short-term contention, leading to delay spikes that are especially detrimental to interactive applications [7]. The intermediate performance of mixed traffic suggests that even partial smoothing of traffic can yield tangible latency benefits, echoing earlier workload characterization studies [6].

Queue discipline emerged as a decisive factor under high-load conditions. The consistent reduction in jitter and tail latency observed with RED compared to Drop Tail supports established arguments for active queue management as a means to control buffer inflation and stabilize delay distributions [12, 16]. The statistically significant Queue × Load interaction further indicates that queue management choices are most consequential precisely when networks are stressed, a scenario common in small deployments with limited overprovisioning [1, 2]. While mesh topologies exhibited slightly higher latency due to longer average path lengths, the results suggest that modest path diversity can still distribute contention and mitigate extreme delays when routing remains stable, consistent with routing architecture principles [14]. Overall, the simulation-based approach validated in this research demonstrates that controlled traffic modeling can reveal latent performance bottlenecks before deployment, addressing a documented gap in small-network-focused latency analysis [5]. By integrating factorial statistical analysis with traffic simulation, the research provides empirical grounding for configuration decisions that are often made heuristically in practice [10, 11].

Conclusion

This research provides a systematic examination of latency patterns in small-scale computer networks using simulated traffic, demonstrating that delay behavior in such environments is highly sensitive to offered load, traffic variability, topology, and queue management choices. The results confirm that latency growth is inherently nonlinear as utilization increases, with sharp escalation beyond moderate load levels, underscoring the fragility of small networks operating close to capacity. Bursty traffic was shown to disproportionately amplify both average and tail delays, highlighting the risks associated with unregulated or highly variable workloads in environments that lack sophisticated traffic engineering. At the same time, the research illustrates that configuration-level interventions can meaningfully improve performance without requiring hardware upgrades. In particular, the consistent reduction in jitter and tail latency achieved through active queue management demonstrates that selecting appropriate queue disciplines is one of the most effective levers available to administrators of small networks. From a practical perspective, these findings suggest that network designers and operators should proactively evaluate latency under realistic, bursty traffic rather than relying on average-load assumptions, and should treat queue configuration as a first-order design decision rather than a default setting. For educational laboratories and small organizations, adopting simulation-driven pre deployment testing can help anticipate performance limits, validate topology choices, and identify safe operating margins for latency-sensitive applications. Incorporating modest path diversity where feasible can further enhance resilience to congestion, provided routing remains stable. Practically, administrators should aim to operate small networks below critical utilization thresholds, deploy active queue management by default on bottleneck links, and periodically reassess traffic characteristics as application mixes evolve. Embedding these practices into routine planning and training can reduce the likelihood of unexpected latency degradation, improve user experience, and enable evidence-based tuning as network demands grow. Ultimately, the research demonstrates that even within constrained budgets and simple infrastructures, informed design and configuration choices guided by simulation and basic statistical analysis—can substantially enhance the predictability and robustness of latency performance in small-scale networks.

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