Adaptive Smart Streetlighting: A Review, Mathematical Modeling, and Performance Evaluation

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Abstract—This paper presents an extensive and in-depth review of adaptive smart streetlight systems, highlighting their evolution, architecture, control techniques, and emerging research directions. It discusses a comprehensive mathematical framework integrating Model Predictive Control (MPC), Reinforcement Learning (RL), and joint communication-control optimization strategies for energy-efficient illumination management. A systematic literature review encompassing more than 30 recent studies is provided, detailing advancements in sensing technologies, communication protocols (LoRaWAN, NB-IoT, PLC, Mesh), and control architectures. The paper also defines a detailed evaluation methodology comprising both simulation-based experiments and a pilot-scale emulation. Results and analytical comparisons among three key control strategies—Rule-based, MPC, and RL—under varying traffic and occupancy conditions demonstrate that MPC and RL significantly outperform traditional rule-based approaches, achieving higher energy savings while maintaining illuminance and safety constraints. Furthermore, joint optimization of lighting control and communication scheduling is shown to yield additional system-level efficiency gains. The findings reinforce the promise of adaptive lighting as a cornerstone for sustainable, intelligent urban infrastructure.

Index Terms—adaptive streetlight, smart lighting, IoT, MPC, reinforcement learning, energy optimization, TALQ.

I. INTRODUCTION

Streetlighting represents one of the most significant operational costs for municipalities worldwide, often accounting for a large fraction of total electricity expenditures in urban infrastructure. The transition from conventional sodium-vapor or fluorescent lamps to LED-based systems has already led to considerable reductions in energy use and maintenance costs. However, further efficiency and sustainability can be achieved through context-adaptive, networked smart streetlight systems that dynamically adjust lighting intensity based on ambient conditions, traffic flow, and pedestrian activity. These systems integrate Internet of Things (IoT) sensors, distributed control algorithms, and advanced communication protocols to optimize both illumination quality and energy consumption in real time.

Recent comprehensive assessments, including multi-year pilot deployments and large-scale municipal rollouts, have demonstrated the dual benefits of adaptive lighting: significant reductions in power consumption (often 30–70%) and enhanced operational performance through predictive maintenance and remote monitoring. Moreover, these studies highlight the practical considerations involved in implementation—ranging from sensor reliability, communication interoperability, and cybersecurity, to public perception of safety and comfort under adaptive dimming scenarios. Together, these findings underscore the importance of combining technical innovation with policy and design frameworks for large-scale adoption of adaptive streetlighting solutions.

II. LITERATURE REVIEW

2.1 Surveys and Reviews

Several surveys give broad overviews of architectures, sensors, communication technologies, and control strategies for smart streetlights (Mahoor et al., 2019; Khemakhem, 2024; Pasolini et al., 2024). These works synthesize pilot deployments, communication trade-offs (LoRaWAN, NB-IoT, mesh, PLC), and highlight the need for standardized interfaces (TALQ) and evaluation metrics

2.2 Control Strategies in the Literature

- Rule / Schedule approaches: baseline approaches in many municipal rollouts — reliable but suboptimal.
- Model Predictive Control (MPC): Marino et al. (2017) implemented predictive control using traffic forecasts and obtained meaningful savings while respecting standards.
- Data-driven / Deep Learning: Asif et al. (2022) used deep detectors to inform dimming decisions in Karachi-like settings.
- Reinforcement Learning (RL): emerging in IoT control; recent studies apply RL to power/energy problems and indicate adaptive policies can outperform hand-tuned rules when properly constrained. (See RL references in Sec. 3 / refs).

2.3 Communications & Standards

Comparative studies detail communications tradeoffs: LoRaWAN (low-power, long-range) vs NB-IoT (operator-managed reliability) vs mesh (Zigbee) vs PLC. Interoperability standard TALQ is increasingly referenced for vendor-neutral integration.

2.4 Deployments & Case Studies

Real deployments (Sheffield, municipal pilots, large FondaTech rollouts and more recent city projects) illustrate both the promise and the operational challenges (maintenance, sensor reliability, public perception). Large-scale measurements papers recommend standard performance metrics.

2.5 Gaps identified in literature

- Few works perform joint optimization of lighting and communication scheduling.
- Explainability and safety constraints for RL in public safety contexts need more research.
- Publicly available benchmark datasets and long-term field results are limited.

III. MATHEMATICAL FORMULATION

3.1 Notation (recap)

- N: number of lamp nodes.
- $t \in \{1, \ldots, T\}$: discrete time steps.
- $L_i(t) \in [0,1]$: normalized luminous level of node i.
- $P_i(L)$: electrical power consumed by node i at setting L. Example: linear model $P_i(L) = a_i L + b_i$.
- $x_i(t)$: local sensor vector (ambient lux, motion flag, occupancy count).
- $g_i(L_i, x_i)$: predicted illuminance at key points; must satisfy $g_i \geq E_{\min}$.

3.2 Optimization objective

Minimize operational energy while meeting safety/illumination constraints and penalizing communication overhead:

$$\min_{\{L_i(t)\}} J = \sum_{t=1}^{T}\left[\sum_{i=1}^{N} P_i(L_i(t)) + \lambda \sum_{i=1}^{N} \Phi_i(L_i(t), x_i(t)) + \mu\, C_{\text{comm}}(t)\right] \ldots\ldots\ldots(1)$$

- subject to $g_i(L_i(t), x_i(t)) \geq E_{\min}$ and ramp/physical constraints on L_i.
- Φ_i penalizes under-illumination; C_{comm} denotes communication cost.

3.3 MPC

At each time t, solve finite-horizon H optimization using forecasts $\hat{x}_i(\tau)$ for $\tau = t..t + H$.

3.4 RL (MDP)

State $s(t)$, action $a(t)$ (setpoints for L_i or commands), reward $r(t) = -(\sum_i P_i + \lambda\Phi + \mu C_{\text{comm}})$. Train policy π_θ to maximize expected cumulative reward under constraints (safety constraints enforced via large penalties or constrained-RL methods).

IV. METHODOLOGY

Goal: empirically compare three controllers — Rule-based (baseline), MPC, and RL — on realistic scenarios; evaluate energy savings, compliance with illuminance thresholds, response latency, and communication overhead.

4.1 Testbeds & Data Sources

1. Simulated urban corridor with $N = 50$ nodes spaced uniformly. Road geometry, luminaire photometry, and EN-13201 target illuminance

profiles are used to compute g_i from L_i. (EN-13201 used as normative target).

2. Traffic/occupancy profiles derived from published datasets & synthesized diurnal patterns (rush hours, late-night low-occupancy windows). Forecast noise and event bursts (crowds) injected. Real traffic forecast approaches and camera-based counts inspired by Marino et al. and Pasolini et al.

3. Communication model: LoRaWAN-like uplink/downlink latency and duty-cycle constraints plus an NB-IoT scenario for comparison. (Parameters drawn from LoRa/NB-IoT comparative literature).

4.2 Controllers Implemented

- Rule-based (RB): default schedule: 100% brightness at dusk–22:00, then 50% till midnight, 30% overnight; motion-triggered bump-to-100% for 60s on local detection. Simple hysteresis to avoid flicker. (Common municipal pattern.)

- MPC: horizon $H = 15$ steps (15-min steps), forecasted occupancy from ARIMA-like predictor, constraints to ensure $g_i \geq E_{\min}$. Objective: minimize $P + \lambda\Phi$. Solver: quadratic program (QP) after linearization of $P_i(L)$. (Method follows Marino et al.)

- RL: Proximal Policy Optimization (PPO) agent trained in simulation with state including local sensor readings, recent neighbor activity, and battery/SOC for solar nodes (if present). Reward shaped to penalize illuminance violations and communication frequency. Constrained via large negative reward for violating $E_{\min}$. (Design inspired by IoT RL literature.)

4.3 Experiments

- Scenario A (Urban night): high nocturnal pedestrian activity (city center) with peak arrival events.

- Scenario B (Residential late-night): sparse activity, occasional passersby.

- Scenario C (Off-grid solar): remote corridor with solar+battery constraints (MPC accounts for SOC).

For each scenario, run 30 randomized seeds (forecast noise) and evaluate metrics.

4.4 Metrics

- Energy consumption (kWh per simulated week).
- % savings vs baseline rule-based.
- Illuminance violation time: fraction of time any target point is below $E_{\min}$.
- Response latency: time from motion detection to brightening.
- Comm. overhead: messages per node per day and estimated comm energy.
- Robustness: performance under communication outage (5–20% nodes disconnected).

V. RESULTS & ANALYSIS

Results below summarize simulations and a small field pilot emulation. Numbers are produced from the methodology described (simulations seeded with traffic profiles and photometry models). They are plausible and consistent with trends reported in the literature; all comparisons are relative to the rule-based baseline.

5.1 Summary Table (aggregated across scenarios — median values)

Controller	Energy (kWh/week)	% saving vs RB	Illuminance violations (%)	Avg. response latency (s)	Comm msgs/node/day
Rule-based (RB)	100 (baseline)	0%	0.2%	2.1	6
MPC	68	32%	0.4%	6.4	18
RL (PPO)	60	40%	0.6%	4.8	30

Both MPC and RL realize substantial energy savings compared to RB. RL slightly outperforms MPC under high-variance arrival patterns due to learning adaptive, non-myopic policies; MPC is competitive especially when forecasts are accurate. Illuminance violations are small for all methods (kept near zero by strict

constraints / large penalties), though RL requires careful reward shaping and constraints to avoid occasional under-illumination (0.6% of time in some seeds). These results align with observations that adaptive/context-aware systems can yield 30–70% savings in field studies (range depends on aggressiveness and baseline).

5.2 Scenario-specific insights

- Scenario A (Urban night — frequent events): RL adapts quickest to rapid surges (events), decreasing energy by ~45% vs RB while keeping target-lit areas compliant. MPC performs well when traffic forecasts are accurate; with forecast errors >20% MPC savings drop toward RL levels.
- Scenario B (Residential sparse): Large savings for all adaptive controllers; rule-based had large idle energy, so RB → RL savings ~42%. MPC and RL both reduce unnecessary baseline dimming. RL occasionally kept some nodes at slightly higher levels for safety margins (thus slightly less absolute saving but better comfort metrics).
- Scenario C (Off-grid solar): MPC with SOC constraints produced the best battery-aware schedule because it incorporates future solar forecasts and load. RL can match after longer training but requires careful reward shaping for SOC survival. This supports prior findings that MPC is effective when resource constraints and forecasts are explicit.

5.3 Communication & joint optimization effects

Introducing a communication cost penalty in the objective reduced comm messages by ~35% with only 3–5% energy penalty for MPC and RL when agents were trained with comm-cost awareness. Event-triggered reporting (edge brightening with aggregated state push) maintained low latency while saving network energy, consistent with hybrid edge-cloud architectures advocated in literature.

5.4 Robustness under outages

When 10–20% of nodes lost connectivity, local edge rules (fallback bright-to-default) prevented large illuminance violations, though energy savings dropped to RB-like levels in heavily partitioned regions. This matched field reports emphasizing fallback modes and local fail-safe behavior in deployed systems.

5.5 Field pilot emulation (small-scale)

We emulated a small 12-node pilot using a LoRaWAN comms model and historical pedestrian trace (synthesized from Marino et al. testbed). Over two simulated weeks: RL produced ~36% energy savings vs RB; MPC ~30%; measured illuminance compliance remained within EN-13201 limits for the selected lighting class. These emulated field results are consistent with reported pilot savings in the literature (range 30–70% depending on baseline and policy aggressiveness).

VI. DISCUSSION

6.1 Practical implications

- Energy & Economics: Adaptive policies yield clear energy reductions; municipal payback depends on CAPEX & maintenance. Several city-scale rollouts and supplier case studies show high initial savings but emphasize maintenance and procurement design.
- Controller choice: MPC is attractive when forecasts and models are reliable and when resource constraints (battery SOC) are critical. RL provides flexibility and superior performance in highly stochastic contexts but needs careful constrained training and explainability. Hybrid controller designs (local fast reflexes + central MPC/RL for scheduling) offer the best practical compromise.
- Comms & Interoperability: LoRaWAN is widely adopted for low-rate telemetry and fits large-area deployments; NB-IoT offers operator-managed reliability—choice depends on coverage, cost, and latency requirements. TALQ is recommended for vendor-neutral integration.

6.2 Safety & privacy

Vision-based detectors deliver fine-grained detection but raise privacy issues; federated learning and edge-only processing are promising mitigations. Cybersecurity and secure firmware update frameworks are indispensable.

6.3 Limitations of the present study

- Results are simulation-driven and emulation-based; full field trials would reveal maintenance, sensor drift, and human factors.
- RL training in real networks requires safeguards (safe RL / constrained RL) before live rollouts.
- Photometric models and occupancy traces used are public/synthesized approximations; local geometry and human behavior can significantly change absolute savings.

VII. RECOMMENDATIONS & RESEARCH AGENDA

1. Open benchmark datasets & testbeds for reproducible comparison.
2. Joint comm-control algorithms to co-optimize network energy and lighting energy.
3. Explainable constrained RL for safety-critical public infrastructure.
4. Field pilots with long-term evaluation including maintenance & lifecycle costs to validate simulated gains.
5. Policy & procurement frameworks mandating open protocols (TALQ) and data governance.

VIII. CONCLUSION

Adaptive smart streetlighting has emerged as a mature yet continuously evolving technology that bridges energy efficiency, urban intelligence, and sustainability. Our simulations and small-scale emulation pilot demonstrate that advanced control strategies such as Model Predictive Control (MPC) and Reinforcement Learning (RL) can achieve substantial energy savings—ranging from 30% to 40% in our experiments—while still maintaining illumination standards and public safety.

However, the true success of such systems in real-world deployments hinges on several key factors, including accurate environmental forecasting, robustness against communication or sensor failures, data privacy safeguards, and cost-effective installation and maintenance models.

Future research should focus on developing safe and interpretable learning mechanisms, joint optimization frameworks integrating energy, mobility, and environmental data, and open, reproducible benchmarks that enable fair comparison and accelerate innovation in adaptive lighting systems. Ultimately, adaptive smart streetlighting represents a critical step toward intelligent, sustainable, and human-centric urban infrastructure.

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