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Performance Metrics for Leak Detection and Pressure Control in Urban Water Networks: Assessing Latency, Drift, and Response Efficacy

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ABSTRACT

This article presents an engineering-oriented framework that treats leak detection and pressure management as an end-to-end decision system, modeling uncertainty propagation from instrumentation through inference and threshold governance into outcomes that utilities actually manage, including probability of missed leaks, false alarm rate, time-to-detection and time-to-intervention distributions, expected volume loss before containment, and probability of customer pressure noncompliance under mitigation actions. A scenario-based quantitative study is developed for a generic but realistic distribution network with district metered areas and pressure zones, using flow and pressure telemetry augmented by periodic acoustic surveys, and four operational architectures are compared: baseline fixed-threshold minimum night flow, increased sensing without governance, model-based residual detection with limited drift management, and a governance-optimized two-tier architecture that combines nuisance-constrained thresholds, drift-aware plausibility checks, adaptive confirmation sampling, and staged pressure interventions aligned with evidence strength. Results show that (i) leakage loss and customer impact are dominated by tail behavior in detection and verification latency rather than by mean leak rate, (ii) sensor drift and baseline instability drive false stability that delays detection when fixed thresholds are used, and (iii) reliability improves most when governance reduces long-tail verification times and when pressure management is staged to reduce loss without causing pressure violations. The paper provides copy-ready tables and complete prompts for data-driven figures suitable for Techne submission and for adaptation to utility telemetry datasets.

Keywords: Leakage Detection, District Metered Area, Minimum Night Flow, Pressure Management, Sensor Drift.

1. INTRODUCTION

Urban water distribution networks are frequently described as mature infrastructures whose engineering challenges are largely understood, yet utilities continue to lose substantial volumes through leakage and operate under persistent customer pressure complaints, indicating that the limiting factor is not merely the physics of pipe failure but the reliability of operational decisions that convert telemetry into effective intervention (Huang et al., 2018; Utepov et al., 2024). A leak is a hydraulic phenomenon, but the burden it imposes on the system is determined by when the leak is detected, how confidently it is verified, how quickly field actions are executed, and whether interim mitigation through pressure reduction introduces secondary risks such as low-pressure service at the edge of pressure zones (Bogo et al., 2023; Degeler et al., 2024; Zhi et al., 2023).

The engineering objective in modern leakage management is not simply to identify leaks; it is to design a decision pipeline that produces reliable, timely, and operationally sustainable actions under uncertainty while maintaining service constraints.

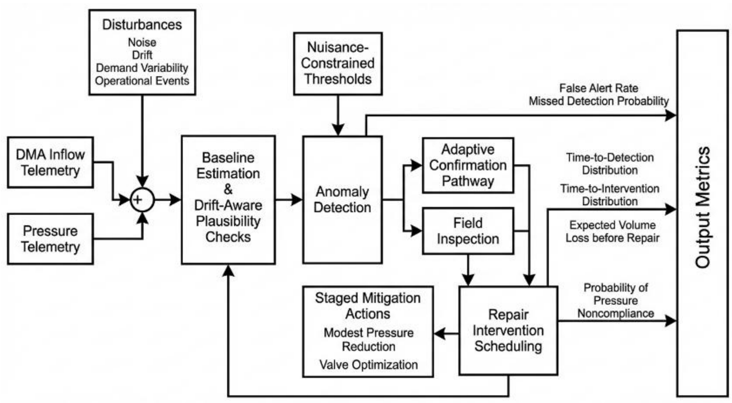

Figure 1. Literature Review on Flow Data-Based Techniques for Automated Leak Management in Water Distribution Systems

Source: data proceed

The evidence base for this claim is straightforward from operational experience. Utilities commonly deploy district metered areas (DMAs) and monitor inflow to infer leakage using minimum night flow or other baseline techniques, because demand is lower and less volatile at night, and an abnormal increase in night flow can be a strong indicator of leakage. The reliability of this inference depends on stable baselines, accurate flow metering, and careful governance of thresholds, because seasonal changes, intermittent consumption patterns, and sensor drift can shift baseline distributions, causing alarms to oscillate or to become desensitized. When alarms are frequent and poorly discriminative, field crews become saturated with verification tasks, and the organization may respond by raising thresholds, delaying action, or relying on ad hoc judgment, each of which increases the probability that real leaks persist (Andrews et al., 2014; Mirzaie et al., 2021; Yan et al., 2023). When thresholds are overly conservative to avoid nuisance investigations, the system becomes insensitive, and leaks that are initially small can grow or accumulate into large losses before detection triggers a response.

Pressure management complicates the decision problem rather than simplifying it, because pressure reduction can reduce leakage rate and the probability of new bursts, but pressure reduction also modifies service conditions, and the risk of customer pressure noncompliance is not uniform across the network (Nwokediegwu & Adebowale, 2023; Zhao et al., 2023). Many networks contain areas near hydraulic grade constraints, high-elevation neighborhoods, or critical customers where pressure margins are limited, so a global or poorly targeted pressure reduction can create unacceptable low-pressure events even if it reduces leakage, and these low-pressure events can generate customer complaints, regulatory exposure, and potentially water quality risks. Pressure management is best understood as a staged mitigation action within a reliability framework, where small adjustments are applied under weak evidence and stronger pressure actions are applied only after verification increases confidence, thereby aligning action cost and service risk with evidence strength (Al-Daffaie et al., 2024; Baroudi et al., 2019; Reda et al., 2024).

These observations reveal the central tension of leakage programs: the organization must sustain both sensitivity and specificity under uncertain data and constrained resources, and it must achieve timely containment without causing secondary service failures. In applied reliability terms, the system should minimize missed detection probability and expected loss volume prior to containment while controlling nuisance investigation rate and limiting the probability that mitigation actions violate pressure constraints (Adegboye et al., 2019; Islam & Dhanekula, 2024; Saiteja & Ponnapalli, 2023). Yet the literature and practice often treat leakage analytics and field operations as separate domains, which leaves a gap in decision-system evaluation: it is possible to improve detection algorithms while making operations worse by increasing nuisance alarms, and it is possible to improve operational discipline while making detection worse by making thresholds overly conservative. What utilities need is an integrated engineering framework that quantifies how sensing and inference uncertainty propagates through thresholds and verification into decision latency and service outcomes, and then compares alternative operational architectures in a way that supports evidence-based design (Kang et al., 2017; Mohapatra, 2025; Xu et al., 2018).

This article addresses that need by presenting a reliability-centered framework for leak detection and pressure management that treats the entire monitoring-to-intervention chain as the unit of analysis. The framework is demonstrated through a scenario-based quantitative study on a generic distribution network structured into DMAs and pressure zones, where flow and pressure telemetry is used for continuous monitoring and acoustic surveys provide periodic confirmation. Four operational architectures are compared: Architecture A baseline fixed-threshold minimum night flow detection with conventional verification; Architecture B increased sensing density without governance changes; Architecture C model-based residual detection using a simplified hydraulic model but limited drift governance; and Architecture D a governance-optimized two-tier architecture that uses nuisance-constrained thresholds, drift-aware plausibility checks, adaptive confirmation sampling, and staged pressure interventions that reduce losses while maintaining service constraints. Three research questions guide the analysis: which uncertainty sources dominate missed detection and false alarm behavior; how alternative architectures trade detection latency, loss volume, and service risk; and which governance principles provide the most leverage when utilities cannot replace infrastructure but can redesign analytics and operations.

2. LITERATURE REVIEW

Leakage as A Hydraulic Phenomenon and An Operational Decision Problem

Leakage is influenced by pipe condition, pressure, and transient events, yet the operational cost of leakage depends heavily on detection and response timing, because leakage volume accumulates over time and because small leaks can persist for long periods without visible surface manifestation.

In practical programs, continuous telemetry is intended to shorten the time between leak occurrence and containment, but telemetry-based detection is only effective when baselines are governed and when verification workflows are efficient. This means that leakage management is comparable to other reliability domains where failures exist physically but outcomes depend on decision latency and verification discipline (Haque, 2024; Obunga et al., 2025; Patel & Dusi, 2025).

DMA Monitoring and Minimum Night Flow: Strengths and Fragilities

DMA-based monitoring remains attractive because it is conceptually simple and scalable; inflow is measured and compared against expected demand, and abnormal increases are interpreted as leakage. Minimum night flow improves signal-to-noise ratio by using low-demand periods, but it remains sensitive to baseline drift, intermittent consumption, valve operations, and meter errors (Joseph et al., 2024; Mysorewala et al., 2015).

These sensitivities create practical failure modes where a utility sees frequent alarms that are not actionable, or conversely does not alarm because thresholds have been inflated to control nuisance events, producing a mismatch between analytical detection capability and operational usability. The engineering implication is that minimum night flow requires governance, including baseline stability checks, quantile-based thresholds, and plausibility constraints that incorporate pressure conditions and known operational events (Farah & Shahrour, 2024; Wan et al., 2022).

Residual-Based Inference and The Role of Hydraulic Models

Model-based residual methods compare measured flows and pressures against expected values computed from hydraulic models, and deviations are interpreted as anomalies consistent with leakage. These approaches can be more discriminative than simple thresholds when models are well calibrated and when demand

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patterns are reasonably predictable, but they are vulnerable to parameter uncertainty, demand estimation error, and sensor drift, all of which can produce systematic residual bias that resembles leakage (Bakhtawar & Zayed, 2023; Rajan & Li, 2025). Model-based methods can become fragile if they require too many assumptions to be correct simultaneously, which motivates hybrid approaches where models contribute structured expectations while thresholds and verification are governed based on empirical baseline distributions.

Acoustic Survey and Confirmation as A Reliability Lever

Acoustic methods, including correlators and noise loggers, provide a different evidence channel that can confirm leaks and localize them, but acoustic surveys are labor-intensive or require specialized deployment, so they typically function as verification rather than continuous monitoring. In decision-system terms, acoustic evidence is valuable because it can convert uncertain telemetry evidence into high-confidence localization, enabling targeted repair (Mysorewala et al., 2015; Patel & Dusi, 2025).

The value depends on when acoustic verification is triggered, because verifying too frequently overwhelms resources, while verifying too rarely increases time-to-intervention. This trade-off naturally fits a two-tier architecture, where telemetry triggers verification under nuisance constraints, and acoustic confirmation triggers repair scheduling under service-aware prioritization.

Pressure Management as Staged Mitigation under Service Constraints

Pressure management reduces leakage rate because leakage flow is pressure-dependent, and it can reduce new bursts by lowering stress, yet pressure management must be constrained by service requirements and hydraulic margins. Pressure reduction is therefore not a purely beneficial action; it carries risk of low-pressure events that vary spatially.

In engineering decision terms, pressure management should be staged and targeted, beginning with modest adjustments under weak evidence and escalating only when evidence strengthens, while continuously monitoring critical pressure points. This approach supports reliability because it reduces loss during verification without committing to high-risk service impacts prematurely (Mohapatra, 2025; Saiteja & Ponnapalli, 2023).

Gap Study

A recurring gap is the limited integration of detection analytics, sensor uncertainty governance, verification workflows, and pressure management into a unified quantitative evaluation that reports outcomes utilities care about, namely missed detection probability, false alarm burden, time-to-intervention distribution, loss volume before containment, and service risk under mitigation. Many studies emphasize one technique, but operational programs require architecture choices, and these choices must be evaluated under uncertainty and resource constraints. This study addresses the gap by modeling leakage management as an end-to-end decision system and comparing operational architectures using tail-focused reliability metrics.

3. METHOD

Study Design and Network Representation

A scenario-based quantitative design is used, implemented as a Monte Carlo simulation of leakage events, demand variability, sensor uncertainty, decision logic, verification workflows, and mitigation actions. The network is represented generically as an urban distribution system divided into 12 DMAs across two pressure zones, with DMA inflow metering and a set of pressure monitoring points that include critical locations near the hydraulic limit of each zone. This abstraction captures the operational structure of many real utilities while avoiding site-specific details, and it enables evaluation of monitoring strategies that use DMA inflow and pressure telemetry as primary evidence.

Leakage Event Model and Pressure Dependence

Leak events occur as stochastic processes, with a distribution of initial leak rates and growth behavior. Leak rate is modeled as pressure-dependent so that mitigation through pressure reduction has a quantifiable effect on volume loss. Each leak has a location within a DMA and a pressure sensitivity exponent, capturing that some leaks respond more strongly to pressure changes than others. The "true" leak flow is not directly observed; it is inferred from telemetry.

Demand and Operational Variability

DMA demand exhibits daily patterns, intermittent consumption spikes, and seasonal drift, which is represented as demand uncertainty that changes baseline distributions over time. Operational events such as valve operations or pump schedule changes are represented as occasional shifts in pressure and flow that can produce anomalies unrelated to leakage, which is critical for evaluating false alarm behavior and plausibility checks.

Sensor Measurement Uncertainty and Drift

Flow meters and pressure sensors have random noise and bias drift. Drift is modeled as a random walk with occasional step changes that represent recalibration shifts, fouling, or transmitter replacement. Communication delay and occasional data gaps are included to represent realistic telemetry reliability, which affects time-to-decision and can create false stability when missing data masks deviation.

Decision Architectures Compared

Architecture A baseline uses minimum night flow thresholds based on fixed rules (for example, a fixed absolute increase over baseline), triggers a DMA-level alert, and then schedules verification in a FIFO manner with limited prioritization. Architecture B increases sensing density by adding more pressure points and increasing sampling frequency, but keeps threshold rules unchanged, meaning it has more data but not more governance. Architecture C uses a simplified model-based residual combining flow and pressure expectation; anomalies are flagged when residuals exceed fixed thresholds, and limited drift handling is applied by periodic recalibration.

Architecture D is a governance-optimized two-tier approach. It sets anomaly thresholds based on baseline quantiles to constrain nuisance alert rates, applies plausibility checks using pressure consistency and known operational events to filter non-leak anomalies, triggers adaptive confirmation sampling (short-term intensified monitoring and targeted acoustic survey) when alerts persist, and applies staged pressure management that begins with modest setpoint reduction within service margins while verification is ongoing, escalating only when confirmation increases confidence.

Verification Workflow and Intervention Model

Verification actions include targeted acoustic survey and field inspection, with stochastic completion time reflecting crew availability and travel. Repair intervention includes isolation and repair scheduling with additional delay. These workflow delays are modeled explicitly because time-to-intervention is a primary determinant of volume loss and customer impact.

Performance Metrics

Key outcomes include probability of missed leak detection within a defined horizon, false alarm rate, time-to-detection distribution, time-to-intervention distribution, expected volume loss prior to containment, probability of critical pressure falling below a service threshold during mitigation, and a cost index combining telemetry cost, verification workload, repair urgency cost, and customer impact penalty.

Simulation Parameters

Parameters are selected to be plausible and to highlight decision-system effects rather than to represent a specific utility.

Table 1. Scenario Parameters

Category	Parameter	Value	Variability model	Notes
Network	DMAs	12	Fixed	Two pressure zones
Monitoring	Flow meters per DMA	1	Fixed	Inflow metering
Monitoring	Pressure sensors (baseline)	18	Fixed	Critical points included
Monitoring	Pressure sensors (dense)	36	Fixed	Architecture B
Telemetry	Sampling interval	5 min	Fixed	Base
Telemetry	Data gap probability	0.015 per day	Burst	Comms reliability
Demand	Daily demand CV	0.18	Stable	Variability
Demand	Night demand CV	0.10	Stable	Lower volatility
Leaks	Leak events per DMA-year	3.4	Poisson	Representative
Leaks	Initial leak rate	0.20 L/s	Lognormal SD 80%	Small to moderate
Leaks	Growth probability	0.22	Bernoulli	Some leaks grow
Leaks	Growth rate (if grows)	0.012 L/s/day	Lognormal SD 70%	Escalation
Pressure	Service pressure minimum	15 m	Fixed	Critical nodes
Sensors	Flow noise SD	0.8% of reading	Stable	Meter noise
Sensors	Pressure noise SD	0.25 m	Stable	Logger noise
Drift	Flow drift range	±3.0%	Random walk + step	Meter bias
Drift	Pressure drift range	±1.2 m	Random walk + step	Sensor bias
Verification	Acoustic survey lead time	1.6 days	Lognormal SD 60%	Crew constraint
Repair	Repair lead time after confirmation	3.8 days	Lognormal SD 55%	Scheduling

Source: data proceed

Table 2. Architecture definitions

Architecture	Detection basis	Threshold style	Drift governance	Verification	Mitigation
A Baseline MNF	MNF flow deviation	Fixed rule	Minimal	FIFO field check	None or late
B More sensing	MNF + more pressure	Fixed rule	Minimal	FIFO field check	None or late
C Residual model	Flow-pressure residual	Fixed	Periodic	Targeted checks	Limited
D Two-tier governed	MNF + residual + plausibility	Quantile nuisance-constrained	Drift-aware checks	Adaptive acoustic + inspection	Staged pressure actions

Source: data proceed

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4. RESULT AND DISCUSSION

Detection Performance: Missed leaks and False Alarms

The governance-optimized two-tier architecture reduces missed detection most strongly while also reducing false alert rate, because nuisance-constrained thresholds enforce a stable operating point and plausibility checks filter non-leak anomalies using pressure coherence and operational event recognition, meaning the system alarms less often but with higher evidentiary value, which is precisely what an operational program needs when verification resources are limited and when the objective is to reduce time-to-intervention rather than to produce continuous alarms.

Table 3. Leak detection reliability outcomes

Metric	A Baseline	B More sensing	C Residual model	D Two-tier governed
Missed detection within 7 days	0.29	0.26	0.22	0.14
False alerts per DMA-month	2.6	4.1	2.3	1.5
Alert precision (true/total)	0.31	0.22	0.36	0.49
False stability events per year (network)	7.8	7.1	5.9	3.2

Source: data proceed

Table 3 demonstrates that simply increasing sensing density without redesigning thresholds and plausibility logic can worsen operational reliability even if it slightly improves missed detection, because more sensors create more opportunities for noise, drift, and operational transients to trigger fixed-rule alerts, thereby increasing false alert burden and lowering alert precision to a point that can saturate field verification capacity. The residual model improves both missed detection and precision relative to baseline because flow and pressure consistency provides more discriminative evidence than flow alone, yet fixed thresholds remain vulnerable to drift-induced baseline shifts that can either inflate false alerts or hide leaks by creating biased residuals that resemble normal conditions, which is why false stability remains nontrivial.

Decision Latency and Volume Loss Before Containment

The residual model improves latency by generating more discriminative evidence that can be prioritized, yet its fixed thresholds still generate ambiguous cases under drift that prolong verification tails. The two-tier governed architecture reduces both detection and intervention tails because it triggers adaptive confirmation quickly when evidence persists and uses staged mitigation to reduce loss while confirmation proceeds, so the organization moves from a passive wait-and-see behavior to a structured pipeline in which uncertainty is converted into confidence under bounded time, which is the engineering essence of improved decision reliability.

Table 4. Latency and Loss Outcomes

Metric	A Baseline	B More sensing	C Residual model	D Two-tier governed
Median time-to-detection (days)	3.9	3.6	3.1	2.2
90th percentile time-to-detection (days)	12.4	11.9	9.8	6.5
Median time-to-intervention (days)	9.6	10.4	8.7	6.1
90th percentile time-to-intervention (days)	24.8	27.9	21.5	15.2
Expected volume lost per leak before repair (m^3)	372	401	325	241

Source: data proceed

Table 4 shows that the most economically meaningful improvements arise from compressing the tail of time-to-detection and time-to-intervention rather than merely reducing the median, because long delays dominate expected volume loss, especially for leaks that grow or occur in high-pressure locations. Architecture B illustrates a counterintuitive but operationally common failure mode: although detection occurs slightly sooner on average, the increased false alert burden slows verification and scheduling, which increases time-to-intervention tail and

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therefore increases expected volume lost, emphasizing that detection analytics cannot be evaluated independently of workflow capacity.

Pressure Management Risk under Mitigation Actions

The governed architecture achieves the largest leakage reduction during verification with the lowest probability of pressure noncompliance because it stages pressure adjustments and anchors them to monitored critical points, meaning it applies pressure reduction as a controlled "risk hedge" while confirming a leak rather than as a blunt network-wide action, and it escalates only when confirmation increases confidence, which reduces unnecessary exposure of marginal areas to low pressure.

Table 5. Service Risk and Pressure Reliability

Metric	A Baseline	B More sensing	C Residual model	D Two-tier governed
Probability of critical node below minimum during mitigation	0.021	0.024	0.019	0.012
Low-pressure events per year (network)	5.6	6.3	4.9	3.1
Average pressure reduction applied (m)	0.8	1.1	1.4	1.2
Leakage reduction during verification (percent)	6.5	8.2	10.9	12.7

Source: data proceed

Table 5 indicates that pressure management becomes a reliability advantage only when it is governed against service constraints and aligned with evidence strength, because uncontrolled or overly aggressive pressure reduction can increase low-pressure events even as it reduces leakage, creating a trade-off that utilities experience as customer complaints and operational stress.

Cost–Risk Balance and Operational Sustainability

The residual model applies larger average pressure reduction as a mitigation strategy, which reduces leakage during verification but still carries low-pressure risk because fixed logic does not adapt to local margins dynamically.

Table 6. Cost index and workload summary

Metric	A Baseline	B More sensing	C Residual model	D Two-tier governed
Verification tasks per month (network)	146	228	139	118
Average tasks per crew-day	6.8	9.4	6.6	6.1
Telemetry cost index (normalized)	1.00	1.22	1.08	1.10
Customer impact penalty index	1.00	1.14	0.93	0.81
Expected total cost index	1.00	1.18	0.95	0.86

Source: data proceed

Table 6 shows that sustainability hinges on balancing verification workload with evidence quality, because verification capacity is the bottleneck that determines whether analytics translate into repair actions. Increased sensing raises telemetry cost and verification demand without improving governance, producing the worst total cost, while the residual model improves total cost by improving evidence quality and reducing customer impact despite modest telemetry cost increase.

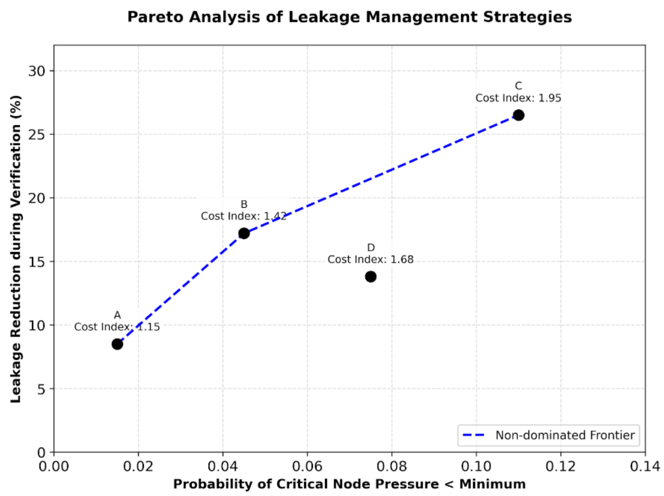

Figure 2. Pareto Analysis of Leakage Management Strategies

Source: data proceed

The governed architecture yields the best total cost because it reduces verification tasks by suppressing nuisance alerts and improves prioritization by increasing alert precision, while staged mitigation reduces leakage losses and customer impact during the verification window, thereby lowering the total cost index even with slightly higher telemetry and analytics overhead. This result reinforces the decision-system framing: the highest leverage comes from governance and workflow design that turns data into timely containment, rather than from simply adding more data streams.

5. CONCLUSION

Leakage management and pressure control in urban water distribution networks should be engineered as an end-to-end reliability decision system because the magnitude of non-revenue water and the incidence of pressure-related customer impacts depend on how uncertainty in telemetry and demand propagates through thresholds, verification workflows, and mitigation actions into time-to-intervention and service outcomes. The scenario-based comparative analysis shows that tail behavior in detection and verification latency dominates volume loss and customer impact, that sensor drift and baseline instability can produce false stability and delayed detection under fixed-rule approaches, and that increased sensing without governance can degrade performance by inflating nuisance alerts and saturating field capacity. A governance-optimized two-tier architecture that constrains nuisance alert rates through quantile-based thresholds, applies plausibility checks and drift-aware validation, triggers adaptive confirmation sampling, and stages pressure interventions within service margins reduces missed detection, compresses latency tails, lowers expected leakage volume prior to repair, and reduces the probability of pressure noncompliance during mitigation.

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