

Data-driven lifecycle governance for intelligent public lighting: a multi-city deployment study

Digital
Transformation
and Society

Sergio Gambacorta

Smart Cities and B2G Innovation Unit, Enel X, Rome, Italy

Received 24 April 2026
Revised 1 August 2026
7 September 2026
Accepted 15 September 2026

Abstract

Purpose – This practitioner case study addresses the persistent gap between smart city aspirations and implementable urban operator practice by examining how artificial intelligence (AI)-enabled methods can be operationalised across the full infrastructure lifecycle within real infrastructure operator workflows.

Design/methodology/approach – The framework integrates four AI-enabled operational tools – GeoAI satellite asset mapping, a fuzzy-logic engine encoding national lighting standards, a Bayesian predictive maintenance model designed for data-scarce contexts and an adaptive lighting control system. The artefacts were deployed and evaluated through naturalistic pilots and retrospective analyses in municipalities in Italy, Spain and Chile.

Findings – Deployment evidence (operationally observed, not from controlled experiments) shows 82–92% asset detection accuracy across sites, ~70% design effort reduction, ~20% maintenance efficiency gain and ~35% energy savings beyond light-emitting diode baselines. Cross-site deployment yielded five transferable design principles for scalable, regulation-aware governance of AI-enabled civic infrastructure.

Practical implications – The framework provides actionable guidance for municipal administrators and infrastructure operators pursuing AI-enabled infrastructure governance, contributing to SDG 7 (Affordable and Clean Energy) and SDG 11 (Sustainable Cities and Communities).

Originality/value – This study contributes an operationally validated governance framework that moves beyond isolated smart city pilots by embedding heterogeneous AI tools into systemic lifecycle management under real-world institutional and regulatory constraints.

Keywords Smart cities, Urban informatics, Public street lighting, Infrastructure management, Geospatial artificial intelligence, Design science research, Digital transformation, Sustainable development goals, AI governance

Paper type Practitioner paper

1. Introduction: from aspirational visions to operational practice

1.1 AI-enabled technologies and the “last mile” problem in urban infrastructure

Cities worldwide are increasingly embracing data and artificial intelligence (AI) as central enablers to address urban challenges and enhance public services. Research in urban informatics has progressively documented this shift: over the past decade, the field has reframed the smart city debate, moving beyond aspirational visions towards reproducible,

© Sergio Gambacorta. Published in *Digital Transformation and Society*. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence may be seen at <http://creativecommons.org/licenses/by/4.0/>

Funding: This research received no external funding.

Competing interests: The author is an employee of Enel X S.r.l., which holds intellectual property rights on patents discussed in this article (Italian Patent no. IT102023000013404, Italian Patent no. IT102024000001155 and International Patent Application WO2025003931A1) and copyrights on images, photos, data and software, including the represented diagrams and designs. The conceptual frameworks, empirical interpretations and design principles as well as any opinion presented reflect the scholarly analysis of the author and do not represent official corporate commitments, views, positions, policies, strategies, decisions, endorsements, commercial warranties or tender specifications of the employer.



Digital Transformation and Society
Emerald Publishing Limited
e-ISSN: 2755-077X
p-ISSN: 2755-0761
DOI 10.1108/DTS-04-2026-0170

evidence-based practices capable of transforming everyday infrastructure management (Batty, 2012; Kitchin, 2018; Shi, Goodchild, Kwan, Zhang, & Batty, 2021). Complementary critical scholarship has emphasised that the value of these practices depends on how data-driven systems are embedded in institutional workflows, on transparency of algorithmic decision-making and on the political economy of urban data (Kitchin, 2013; Kitchin, Cardullo, & Di Felicianantonio, 2019); these socio-technical considerations frame the governance orientation adopted in this study.

The core ambition – integrating digital technologies, data analytics and operational systems to create more sustainable and efficient urban services – has become increasingly actionable as AI tools mature and deployment costs decline (Albino, Berardi, & Dangelico, 2015; Shi, Goodchild, Batty, Kwan, & Zhang, 2022).

This study reports on the operational design and multi-city deployment of an integrated, AI-enabled lifecycle framework for public street lighting. Following the Design Science Research paradigm (Hevner, March, Park, & Ram, 2004), the study formalises transferable design knowledge for data-driven civic infrastructure governance, grounded in operationally deployed artefacts validated across heterogeneous urban contexts in Italy, Spain and Chile.

1.2 Public street lighting as a critical urban infrastructure

Public street lighting is an exemplary domain for operationalising data-driven urban governance. As one of the most pervasive urban infrastructures, it contributes to safety, mobility, urban aesthetics and typically accounts for up to 40% of municipal energy consumption in European cities (Ożadowicz & Grela, 2017), making it a strategic lever for climate mitigation, cost efficiency and service equity. Recent technological progress, particularly the diffusion of light-emitting diode (LED) technologies and Internet of Things (IoT)-enabled controls, has created unprecedented opportunities to reimagine how lighting systems are planned, operated and governed. Yet management practices often remain anchored in legacy modes: asset inventories are updated infrequently through laborious field surveys; design standards are applied inconsistently; maintenance is predominantly reactive; and luminaires operate at fixed brightness levels regardless of actual demand. These limitations reveal clear innovation opportunities: multi-source data, predictive algorithms and adaptive control can transform conventional lighting into responsive civic infrastructure (Alvarez, Duarte, Frenchman, & Ratti, 2022).

In many European and Global markets, public lighting infrastructure is planned, operated and maintained by specialised utility operators under long-term service concessions awarded by municipalities. In this governance model, the municipality acts as the contracting authority and service quality evaluator, while the operator assumes end-to-end responsibility for the technical and digital transformation of the infrastructure – making this practitioner study a report on internal operational innovation within an infrastructure management firm, conducted in close alignment with municipal service requirements.

1.3 Lifecycle integration and policy context

Embedding data-driven methods across the full lifecycle – from inventory and planning to maintenance and operation – offers a pathway towards more sustainable, accountable and socially equitable lighting, in line with broader urban goals of resilience and decarbonisation. Recent policy frameworks (e.g. the European Green Deal's energy efficiency targets; European Commission, 2019), empirical studies (e.g. Team Nachlichter, 2025) and technological advances further strengthen the case for rethinking public lighting management beyond isolated interventions. Advancing this transition is directly aligned with SDG 7 (Affordable and Clean Energy) and SDG 11 (Sustainable Cities and Communities), which together call for universal access to sustainable energy services and the provision of safe, resilient and sustainable urban infrastructure (Regona, Yigitcanlar, Hon, & Teo, 2024).

1.4 Addressing the practitioner gap: from isolated pilots to integrated lifecycle management

The proposed framework distinguishes itself from conventional infrastructure operator practices – which rely on manual inventories, reactive maintenance and fixed lighting schedules – by integrating four AI-enabled tools across all infrastructure lifecycle phases (inventory, planning, maintenance, operation) within a single regulation-aware governance system validated through multi-city deployments.

Recent empirical work confirms that legacy practices and absence of data management represent the dominant barriers preventing successful digital transformation of urban infrastructure assets – underscoring the operational urgency of an integrated, lifecycle-wide approach (Lafioune, Poirier, & St-Jacques, 2024). Current literature on smart and adaptive lighting predominantly focuses on isolated algorithmic optimisations – such as sensing technologies, dimming strategies or control algorithms – while offering limited treatment of systemic perspectives capable of aligning data-driven optimisations with the operational governance of the full public lighting lifecycle.

Based on this operational gap, the deployment experience addresses three guiding questions:

- RQ1. How can established urban informatics methods be systematically integrated into a coherent framework supporting the full lifecycle of public lighting infrastructure – from inventory and planning to maintenance and operation – within real urban infrastructure operator workflows?
- RQ2. To what extent can such a framework be operationalised under real-world constraints, including regulatory compliance, legacy systems, data heterogeneity, privacy regulation and institutional governance requirements?
- RQ3. What actionable design principles and governance lessons can be derived from multi-city deployments to support reproducibility and scalability across different urban contexts?

These questions are addressed through a practitioner-research approach that combines the development of interlinked artefacts with their evaluation in real-world urban settings, bridging academic urban informatics and infrastructure practice. This dual contribution – design knowledge and multi-city deployment evidence – positions the study for both scholarly and professional audiences.

It is important to state up front that the framework described here is the product of industrial R&D conducted within an infrastructure operator, not of academic research external to the deployment sites. The four artefacts, the underlying methodologies and two of the operational tools are protected by granted patents owned by that operator. This positionality shapes what this article can and cannot claim. The empirical evidence is grounded in proprietary operational deployments and, where controlled comparisons were not feasible, in retrospective back-testing against internal records; it should be read as deployment evidence rather than as the outcome of independent controlled experiments.

The transferable contribution – and the one the author regards as the article's primary design-knowledge output – is the set of five design principles derived from cross-site operational experience (Section 2.5). Possible concerns about independence, reproducibility and generalisability are addressed throughout by explicit reporting of baselines, sample sizes and validation protocols (Table 2) and by a discussion of positionality and limitations in Section 3.3.

1.5 Contributions and scope

The contribution of this multi-city deployment study is positioned along two distinct axes.

On the empirical axis, it reports deployment evidence from operationally deployed artefacts across municipalities in Italy, Spain and Chile, under heterogeneous regulatory contexts and urban morphologies (consolidated in [Table 2](#)).

On the design-knowledge axis, cross-site deployment enabled the derivation of five transferable design principles ([Section 2.5](#)) extending beyond lighting to civic infrastructures facing similar data-scarcity and institutional constraints. Consistent with the practitioner-research orientation of this study, the framework-level contribution lies in the integration, operational deployment and lifecycle governance of established AI methods, not in the algorithmic novelty of the individual techniques used.

1.6 Framework positioning in the problem-solution space

[Table 1](#) positions the framework within the urban infrastructure problem-solution space, contrasting the multi-artefact approach with conventional municipal practice and the siloed research trajectories often reported in the literature.

This positioning clarifies that the practitioner contribution does not lie in algorithmic novelty: CNNs ([Zhu et al., 2017](#)), fuzzy logic ([Zadeh, 1965](#)), Bayesian networks ([Weber, Medina-Oliva, Simon, & Iung, 2012](#)) and IoT-based smart lighting ([Zanella, Bui, Castellani, Vangelista, & Zorzi, 2014](#)) are all well-established techniques. Adjacent integrated proposals also exist: urban digital-twin architectures for infrastructure decision-support ([Grieves & Vickers, 2017](#)), GeoAI-driven smart-city planning platforms ([Mortaeheb & Jankowski, 2023](#))

Table 1. Framework positioning across core lifecycle phases

Dimension	Prevailing practice or literature	Approach adopted in this framework
Inventory management	Inventories often outdated; manual night surveys are common. Emerging research uses remote sensing for lighting, but few operational deployments	<i>GeoAI-based census</i> : application of established CNN object-detection paradigms (Zhu et al., 2017 ; Li et al., 2022) to nocturnal small-object detection, with GIS-ready outputs suitable for downstream planning workflows
Design and standards	Lighting standards (e.g. UNI 11248) exist but class assignments are done manually by designers; planning is time-consuming and subjective	<i>Computational Policy engine</i> : encodes UNI 11248:2016 as a two-stage fuzzy-logic system producing explainable class assignments
Reactive maintenance	Predominantly reactive (“fix on fail”) or periodic bulk lamp replacement. Some predictive models in research, often requiring IoT sensors, remain pilot-only	<i>Bayesian UQ model</i> : probabilistic failure forecasting relying only on pre-existing administrative and territorial data, without additional IoT instrumentation
Real-time operation	Increasing interest in adaptive lighting (IoT-based dimming). Proven energy savings with LEDs + dimming, but deployments are uneven. Privacy and acceptance concerns for sensor-based control	<i>Adaptive Control Logic</i> : privacy-preserving edge architecture with safety floor enforced at control-logic level
Overall impact	Smart lighting promises energy and cost savings and improved service, but real-world impact varies. Albino et al. (2015) note a gap between smart city visions and actual implementation	<i>Lifecycle-integrated approach</i> : the four artefacts are structured along a sequential inventory → planning → maintenance → operations chain and interface with existing operator workflows. Interoperability constraints and co-benefits (safety compliance, transparency of decision-making) are treated as first-order design requirements rather than as secondary considerations

and DSS-oriented artificial-intelligence-city frameworks (Fistola & La Rocca, 2024) each address subsets of the lifecycle problem space.

Relative to these, the differential contribution of the present work is threefold: (1) explicit coverage of all four lifecycle phases (inventory, planning, maintenance, operation) rather than one or two, (2) regulation-aware computational encoding of a specific national standard (UNI 11248:2016) with an auditable two-stage refinement logic and (3) operation under data-scarce conditions typical of municipalities without pervasive IoT instrumentation, using pre-existing administrative and territorial variables. The contribution is therefore the operational integration and multi-city deployment of these methods within an infrastructure-operator workflow, together with the transferable design knowledge derived from that experience.

2. Operationalising the framework: solutions across the public lighting lifecycle

The proposed framework adopts an integrated, data-driven approach to the public lighting lifecycle, addressing its four core phases: inventory, planning, operations and maintenance.

Consistent with the Design Science Research (DSR) tradition (Hevner *et al.*, 2004), each of the four artefacts is treated as a designed intervention whose relevance is grounded in an identified environmental problem (infrastructure operator practice) and whose rigour is grounded in the knowledge base of urban informatics, GeoAI and probabilistic modelling.

The artefacts were developed and refined through three iterative construction–evaluation cycles – initial prototyping to establish baseline technical feasibility, cross-validation testing framework transferability across regulatory contexts and urban morphologies, and operational consolidation integrating the artefacts into a unified lifecycle governance system – a progression that exemplifies DSR Guideline 6 (design as a search process). Each cycle generated concrete calibration refinements (e.g. CNN training-data augmentation for satellite imagery variation; fuzzy-rule threshold adjustments for regulatory differences) and informed the design principles articulated in Section 2.5. Consistent with DSR Guideline 3 (design evaluation), each artefact was evaluated through the observational and descriptive methods available in a deployment-constrained industrial setting – naturalistic pilots, expert benchmarking and retrospective back-testing against operational records – rather than through the experimental methods available only in fully controlled research environments; this distinction is preserved throughout the results reporting. The subsequent subsections detail each phase, outline the methodology and report the deployment metrics summarised in Table 1.

2.1 Inventory: remote asset mapping

Objective: Develop a scalable, cost-effective method to automatically create an up-to-date inventory of street lighting assets. A reliable inventory is foundational for any modernisation project. Traditional inventories require crews to physically inspect and record each streetlight, a costly and infrequent process that can take months for a mid-sized city.

Methodology: The approach uses high-resolution nighttime satellite images from open (e.g. VIIRS Nighttime Lights) and commercial sources (e.g. Jilin-1 satellites) that capture cities at night, where streetlights appear as bright points. The data fusion layer performs a spatiotemporal alignment between nocturnal radiative intensity and road network topologies, effectively constraining the search space for candidate nodes (Figure 1).

Deep-learning-based object detection in remote sensing is a well-established research area (Zhu *et al.*, 2017; Li *et al.*, 2022), and recent work has specifically explored the detection of small, densely distributed nocturnal features such as streetlights (Levin *et al.*, 2020). The contribution of the artefact presented here therefore lies not in a new detection algorithm but in the integration of spatial road-network priors with off-the-shelf CNN detectors and in the operationalisation of the pipeline into a multi-city municipal

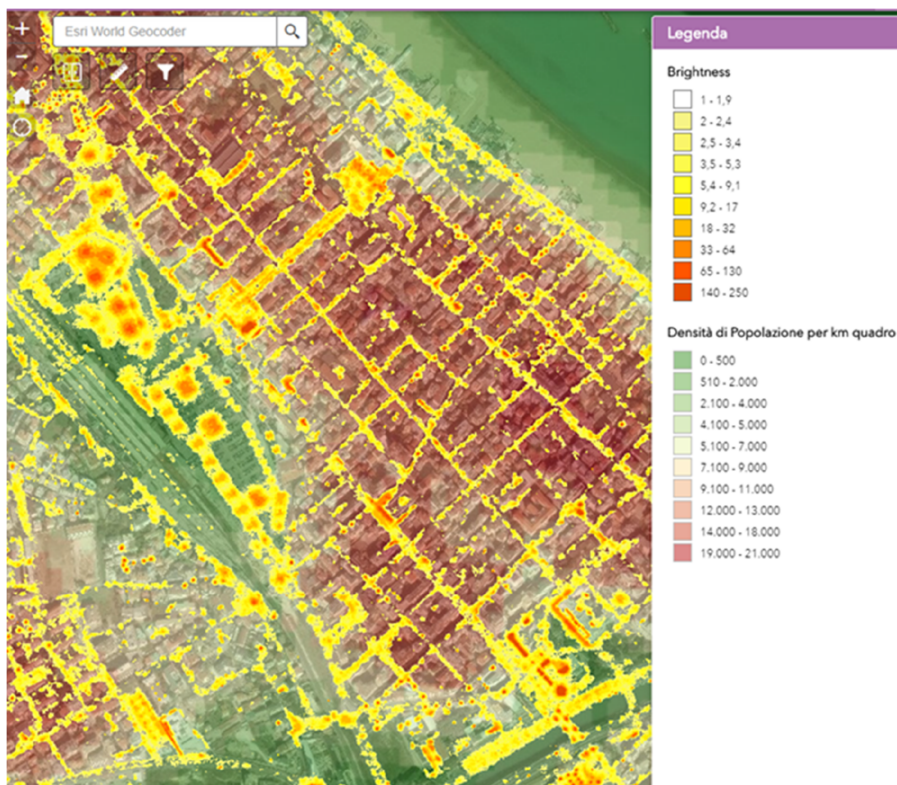


Figure 1. Public lighting – satellite-based census: automated detection of streetlights from satellite imagery, generating a georeferenced lighting asset inventory without field surveys (mid-sized coastal municipality in Central Italy pilot: brightness vs. resident population density alignment)

deployment under naturalistic evaluation. The algorithm also estimates the apparent brightness and colour of each detected light, allowing an approximate classification of lamp type (e.g. LED vs. high-pressure sodium).

Results: The method was validated in pilot deployments in a mid-sized coastal municipality in Central Italy, in a suburban municipality in the Madrid metropolitan area in Spain, and in a high-density municipality in the Santiago Metropolitan Region, Chile. Naturalistic evaluation in the Italian city yielded a detection accuracy of 92.5%, supporting the efficacy of the GeoAI artifact in complex urban morphologies; accuracy was computed as the proportion of streetlights correctly matched within a 3 m tolerance against the city’s GIS-based inventory. Results were validated via a confusion-matrix approach against a ground-truth dataset of 22,122 verified points. The detection performance in Spanish and Chilean cities was similarly high, with accuracy ranging from 82% to 89% (Spain: ~40,000 lighting points; Chile: ~25,000 points). Cross-city variation in accuracy (Italian city 92.5%, Spanish/Chilean cities 82–89%) reflects differences in urban density, spectral resolution of available imagery and ground-truth data quality – a pattern consistent with established remote sensing benchmarks for small-object detection in heterogeneous environments. This yields a major efficiency gain, reducing multi-month field surveys to satellite processing within weeks. This time reduction is reported as an operator-side engineering estimate rather than a formally

measured metric, illustrating operational adoption value instead of a controlled performance benchmark. Ground-truth datasets were provided by pre-existing municipal GIS records maintained independently of the artefact development team. Consolidated numerical results are reported in [Table 2](#).

2.2 Planning: automated design compliance

Objective: Automate and standardise the process of assigning road lighting classes in compliance with official standards. In Italy, for example, UNI 11248:2016 defines lighting requirements based on road category, traffic flow and risk factors.

Normative assignment in conventional workflows suffers from epistemic uncertainty and expert subjectivity, which the proposed computational policy aims to mitigate through rule-based formalisation.

Methodology: The national standard ([UNI 11248:2016](#)) was encapsulated into a fuzzy-logic model to provide consistent, justifiable lighting class recommendations. Unlike “black-box” models, the fuzzy engine embodies an Explainable AI (XAI) by Design approach, providing a human-readable rationale for each class assignment, mapping road attributes to normative requirements through explicit inference rules.

Inputs come from open or routinely collected city data (e.g. OpenStreetMap road hierarchy, traffic proxies, pedestrian crossings, accident history). Architecturally, the system operates through two sequential processing modules, as schematically illustrated in [Figure 2](#). The first module takes road structural characteristics as input – including carriageway width, lane count, speed limit and road functional classification – and generates a conservative baseline lighting category (C1), corresponding to the maximum luminance level compliant with the applicable safety requirements for the road type. The second module refines C1 by incorporating contextual risk modifiers – including the presence and type of pedestrian crossings, road junctions, roundabouts, historical accident and crime data, and the proximity of sensitive facilities (schools, hospitals, municipal buildings) – to produce an optimised design category (C2) whose final luminance level is lower than or equal to C1 while remaining fully

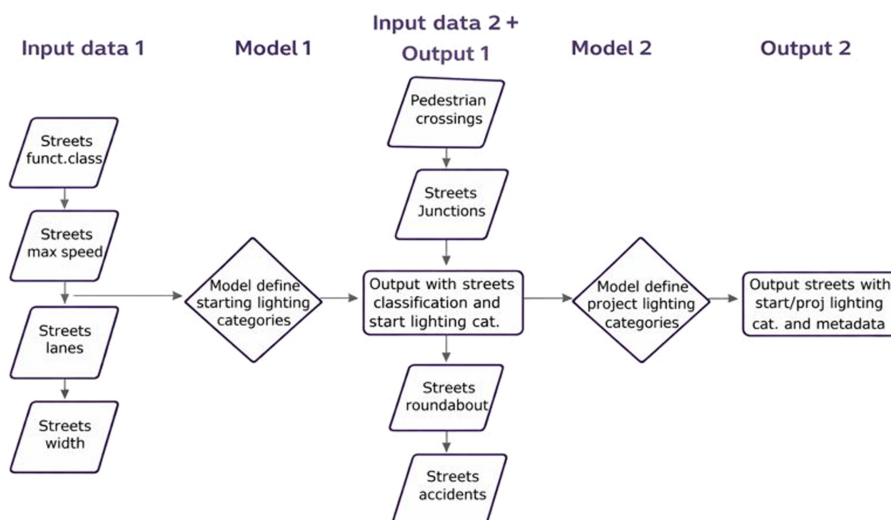


Figure 2. Public lighting – lighting category design tool: conceptual flow diagram of the two-stage fuzzy-logic inference engine (C1 → C2) for normative road lighting classification

compliant with the standard. This two-stage refinement ensures energy minimisation without safety compromise. In cases where specific characteristics are unavailable in open databases, the system applies inferential attribution based on geo-adjacent road segments and reports a quantitative confidence score (expressed as a percentage) reflecting the proportion of characteristics effectively retrieved versus inferred.

This approach, protected by a granted patent (Gambacorta & Becattini, 2025), applies fuzzy logic – a well-established formalism for representing linguistic uncertainty (Zadeh, 1965) – to the encoding of the UNI 11248:2016 lighting standard, and contributes to the broader debate on “computational policy” by showing how design norms can be encoded to support consistency and transparency in urban planning workflows.

Results: The tool was piloted in the design phase for a lighting upgrade project in a suburban municipality in Lombardy (IT), where it auto-generated normative lighting classes for approximately 1,500 road segments. Validation was conducted by two senior lighting engineers with formal responsibility for design compliance in the operator’s engineering unit, who assessed each recommendation against their own independent normative interpretation before comparing outputs (initial independent agreement: 81%). Alignment with expert consensus reached approximately 85% (see Table 2 for the consolidated figures, baseline and validation protocol); the remaining 15% were adjudicated through joint review and documented as edge cases for future rule refinement, providing an auditable baseline for normative compliance.

A human-in-the-loop feedback mechanism allows designers to confirm or correct individual class assignments, with corrections automatically fed back into the model to improve subsequent outputs through supervised learning – progressively reducing the dependence on inferential attribution as deployment experience accumulates.

According to engineering-side estimates shared by the operator’s design team, this automation led to an average reduction of the order of 70% in the design effort required for the class-assignment task. This figure is a professional estimate, not the outcome of formally logged effort measurements, and is reported here as an indication of adoption value rather than as a validated performance metric.

This formalises a normally manual and opaque workflow, enabling transparent, auditable design decisions and evidence-based procurement documentation at municipal scale.

2.3 Operations: adaptive lighting control system

Objective: Dynamically adjust streetlight brightness in real time to save energy and adapt to conditions, without compromising safety. Conventional streetlights run on fixed schedules (dusk-to-dawn or time-based dimming), which can waste energy during low-traffic periods. With LED technology and wireless controls, there is an opportunity to modulate lighting based on actual demand and environmental conditions.

Methodology: The adaptive lighting system integrates IoT-connected luminaires with a small number of area sensors and an edge AI controller. Instead of installing expensive sensors on every lamp, the system uses a few strategically placed low-resolution cameras to monitor traffic and weather conditions in key zones. These cameras do not record identifiable data (addressing privacy concerns); they only count moving objects and analyse weather and luminance. A control algorithm, implemented as a rule-based system determines the optimal illumination level for each zone in real time. Crucially, it always respects safety regulations and technical norms (e.g. maintaining minimum luminance per UNI 11248 standards).

Results: The adaptive system was piloted in a major high-traffic arterial corridor in Northern Italy (Figure 3). On main roads, aggregated measurements over the six-month period indicated an average energy reduction of approximately 35% compared to the pre-adaptive fixed-schedule LED baseline measured in the same zone during the preceding six-month period (with same seasonal profile). This figure represents energy savings beyond the LED retrofit baseline – that is, the incremental gain from adaptive control alone: savings are

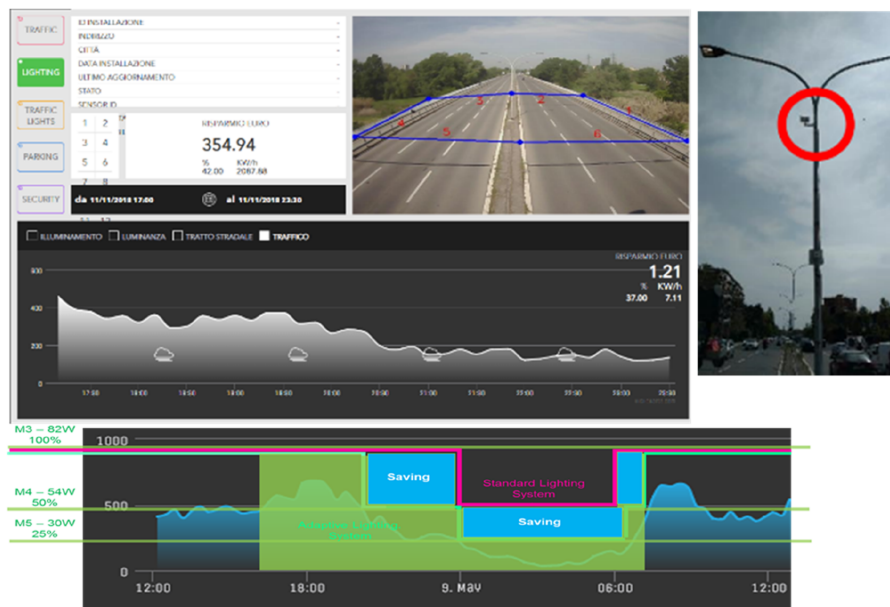


Figure 3. Public lighting – adaptive lighting control interface: real-time dynamic dimming management showing vehicle/weather monitoring (top panels) and energy reduction profiles compared to static LED operation (bottom graph)

attributed to dynamic dimming during low-traffic periods (23:00–05:00) while maintaining minimum luminance thresholds per UNI 11248:2016 standards, with no reported safety incidents or citizen complaints during the pilot. The estimate is therefore a within-site, before/after comparison rather than a randomised A/B experiment. Full context is reported in Table 2.

2.4 Maintenance: Bayesian predictive maintenance model

Objective: Shift from reactive to proactive maintenance by predicting lamp failures in advance. Traditional reactive or scheduled re-lamping approaches are inefficient: reactive repairs cause outages, scheduled replacements waste useful lamp life. The goal was a predictive strategy using data already available to most operators.

Methodology: A Bayesian statistical model was developed to estimate a probabilistic Failure Risk Index for each lighting device within a predefined temporal interval. A defining feature of this approach is that the model operates entirely without data sensed at or by the lighting devices themselves, relying instead on geo-informatic analysis of two categories of pre-existing variables: exogenous variables characterising the territorial context (meteorological conditions, air quality indicators including SO_2 concentration, acid rain exposure and UV radiation, distance from the sea, vandalism risk and topographic features); and endogenous variables characterising the system itself (lamp type and technology, pole configuration, bulb technical specifications, electrical network macro-features including voltage stability and distance from substations and historical maintenance records). The model is structured as a Directed Acyclic Graph (DAG) representing the causal and probabilistic relationships between these variable classes, as schematically illustrated in Figure 4.

The model architecture explicitly incorporates Uncertainty Quantification (UQ) to address both aleatory randomness and epistemic data sparsity within the failure probability distribution. The model is designed as the first stage of a hybrid architecture: when

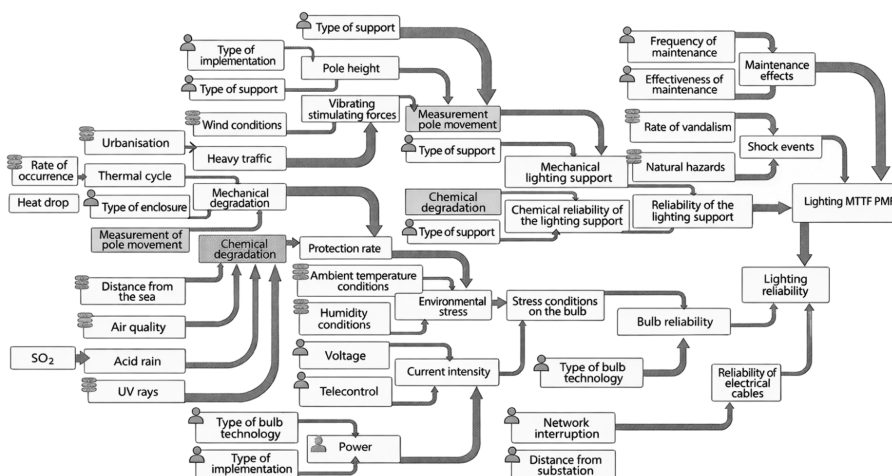


Figure 4. Public lighting – Bayesian Directed Acyclic Graph (DAG) for predictive maintenance: structural representation linking exogenous territorial stressors (environmental, topographic) and endogenous system attributes to failure probability distributions. The terminal distribution node (Lighting MTTF PMF) yields the operational Failure Risk Index used for maintenance scheduling

historical failure data accumulates sufficiently, the Bayesian model can be “reinforced” by a Machine Learning classifier trained on that data, enabling progressively more granular failure predictions at the individual device level. In data-scarce early deployment conditions – the typical situation for most municipal operators – the Bayesian model provides actionable macro-level prioritisation across groups of assets without requiring any IoT sensor infrastructure.

The model produces a ranked list of lamps by estimated failure risk, enabling crews to service the riskiest assets before they fail. The approach has been disclosed via an international patent ([Gambacorta & Ferrara, 2025](#)) and advances the concept of asset management in civic infrastructure by using probabilistic reasoning rather than deterministic schedules ([ISO 55000, 2014](#)).

Results: The Bayesian predictive maintenance model was retrospectively validated through back-testing against 36 months of historical outage and maintenance records from three municipal lighting systems in northern and central Italy (aggregated asset base of the order of 45,000 luminaires). The DAG and priors were defined *ex ante* from failure physics literature and engineering standards, without using the 36-month operational data for calibration. The reference baseline is the actual reactive maintenance intervention log recorded by the operator during that period; the comparator is a simulated intervention schedule derived by following the model’s failure probability rankings on the same historical asset base. Historical failure records used as ground truth were logged by field maintenance crews independently of the model development team. On this basis, adherence to the model’s prioritisation would have reduced reactive maintenance interventions by approximately 20% and produced estimated cost savings in the 15–18% range over the study period (see [Table 2](#)). Because this is a retrospective counterfactual analysis on operator records – the primary evaluation method available in deployment-constrained industrial settings where randomised trials are precluded by service-continuity obligations – the results should be interpreted as operational evidence, not as evidence from a controlled trial.

Table 2. Consolidated deployment evidence across artefacts and sites

Artefact	Site(s)	Sample size/ scope	Baseline of comparison	Primary metric	Reported value	Validation method	Validator independence (internal to operator, independent of dev. team)
GeoAI census (2.1)	Mid-sized coastal municipality, Central Italy	22,122 lighting points	Municipal GIS-based streetlight inventory (pre-existing)	Detection accuracy within 3 m tolerance	92.5%	Confusion-matrix analysis vs. ground- truth GIS	Ground truth maintained by local infrastructure operator engineering team, independent of artefact development team
	Suburban municipality, Madrid metropolitan area (Spain)	~40,000 lighting points			82%		
	High-density municipality, Santiago Metropolitan Region (Chile)	~25,000 lighting points			89%		
Computational policy engine (2.2)	Suburban municipality, Lombardy (Italy)	~1,500 road segments	Independent normative judgement of two senior lighting engineers	Alignment with expert consensus	~85%	Expert benchmarking with adjudication of edge cases	Expert validators from operator engineering unit, independent of artefact development team
Adaptive lighting control (2.3)	High-traffic arterial corridor, Northern Italy	Six-month deployment	Same corridor under fixed-schedule LED operation in preceding six months, matched seasonal profile	Additional energy reduction beyond LED baseline	~35%	Within-site before/ after aggregated measurement	Metering data from operator monitoring system, independent of control-logic team
Bayesian predictive maintenance (2.4)	Three municipal systems, Northern and Central Italy	~45,000 luminaires, 36 months of records	Actual reactive maintenance log	Reduction in reactive interventions	~20%	Retrospective counterfactual back-testing	Historical records logged by field crews, independent of artefact development team
				Estimated cost savings	15–18%	Cost model applied to intervention delta	
Note(s): All figures reported in this table are operational deployment metrics, not the outcome of controlled comparative experiments. Uncertainty around each figure is bounded by data-availability constraints characteristic of proprietary operational settings and should be interpreted in that light. Deployment-adoption indicators reported narratively in the body of the article (e.g. ~70% reduction in class-assignment design effort in Section 2.2 , reduction of asset-inventory turnaround from months to weeks in Section 2.1) are engineering estimates from the operator’s design and field teams rather than protocol-validated measurements, and are not included in Table 2 for that reason							

2.5 Transferable design principles for civic infrastructure governance

The design principles that follow are the primary design-knowledge contribution of this practitioner-research study and should be read as distinct from – though anchored in – the deployment evidence reported in [Sections 2.1–2.4](#) and consolidated in [Table 2](#). Consistent with the Design Science Research tradition ([Hevner et al., 2004](#)), they are proposed as artefact-independent, transferable design knowledge derived from repeated deployment of the four artefacts across heterogeneous municipal contexts (Italy, Spain, Chile) differing in regulatory environment, urban morphology, data availability and institutional culture. Each principle is stated together with (1) the boundary condition it is intended to overcome, (2) the specific deployment site(s) from which the underlying operational experience was drawn and (3) one or two indications of how the principle is expected to transfer to non-lighting civic infrastructure domains. The scope of the claims made for each principle is limited to what the cross-site deployment experience can reasonably support; broader claims of universal generalisability are avoided.

(1) DP1 – Geospatial Network Constraint as Detection Amplifier.

Boundary condition addressed: high false-positive rates in the detection of small, densely distributed urban objects from nocturnal remote sensing in dense morphologies.

Design response: integrate road-network topology as a spatial prior into off-the-shelf CNN detection pipelines, so that the detection search space is constrained by existing GIS layers rather than by additional field surveys or hardware.

Empirical anchor: consistent detection accuracy across three morphologically and instrumentally different sites (mid-sized coastal municipality in Central Italy, suburban municipality in the Madrid metropolitan area in Spain, high-density municipality in the Santiago Metropolitan Region in Chile; [Table 2](#)).

Non-lighting transfer: analogous constraint-based census strategies apply to any urban asset class co-located with mapped spatial structures – for example, roadside urban furniture along road-network graphs, or drainage inspection covers along utility-network graphs – where administrative geospatial layers substitute for hardware-intensive precision sensing.

(2) DP2 – Two-Stage Normative Refinement for Energy-Safe Compliance.

Boundary condition addressed: subjectivity and inconsistency in the manual application of normative standards at municipal scale, coupled with the tension between energy minimisation and safety compliance.

Design response: encode the standard as a two-module fuzzy-logic architecture in which the first stage produces a conservative maximum luminance level (C1) from structural road characteristics alone and the second stage refines it to an optimised minimum compliant luminance (C2) by adding contextual risk factors. Missing attributes are handled through inferential attribution from geo-adjacent segments, with a quantitative confidence score exposed to the operator.

Empirical anchor: ~85% expert alignment and ~70% effort reduction observed across ~1,500 segments in a suburban municipality in Lombardy, Italy ([Table 2](#)).

Non-lighting transfer: the same two-stage regulation-aware pattern is applicable to other jurisdictions where safety-relevant infrastructure standards must be applied consistently at scale – for example, encoding of national road-signage or pedestrian-crossing standards for automated audit workflows – where the first stage guarantees the safety floor and the second stage optimises for a secondary objective (energy, cost, accessibility).

(3) DP3 – Sensor-Free Probabilistic Asset Prioritisation through Territorial Data Fusion.

Boundary condition addressed: the adoption barrier faced by under-resourced

municipalities that need predictive maintenance but cannot deploy pervasive IoT instrumentation upfront. Design response: a Bayesian Directed Acyclic Graph fusing two pre-existing, sensor-free variable classes – exogenous territorial data (meteorology, air quality, coastal proximity, vandalism risk) and endogenous system data (lamp type, pole configuration, electrical network characteristics, maintenance history) – to produce actionable failure-probability rankings, extendable via a downstream ML classifier as records accumulate.

Empirical anchor: retrospective back-testing over 36 months of records on approximately 45,000 luminaires across three northern/central Italian municipal systems (Table 2).

Non-lighting transfer: the sensor-free-then-sensor-augmented pattern is directly applicable to other civic asset classes for which administrative records exist, but continuous monitoring does not – for example, prioritisation of road-surface repair using pavement inventory and climate data, or prioritisation of drinking-water network inspections using pipe-material and soil-corrosivity data – allowing predictive maintenance programmes to start with administrative data and mature with instrumentation.

(4) **DP4 – Privacy-Preserving Edge Architecture for Real-Time Adaptive Governance.**

Boundary condition addressed: the tension between the responsiveness required for adaptive control of public space and the privacy, regulatory and public-acceptance constraints on pervasive high-resolution urban sensing.

Design response: sparse deployment of low-resolution area sensors operating as edge processors, with raw imagery discarded locally and only anonymised aggregated signals transmitted; the safety floor (minimum luminance per applicable standard) is enforced at the control-logic layer before any dimming decision.

Empirical anchor: six-month adaptive-control deployment on a major high-traffic arterial corridor in Northern Italy without reported safety incidents or citizen complaints (Table 2).

Non-lighting transfer: the same “sparse-edge + regulatory floor at control level” pattern is applicable to other adaptive public-space services subject to privacy regulation – for example, adaptive urban HVAC or ventilation control based on aggregated occupancy signals rather than identifiable video – where a hard regulatory constraint must be embedded in the control layer rather than delegated to post-hoc procedural oversight.

(5) **DP5 – Lifecycle artefact complementarity as an information governance chain.**

Boundary condition addressed: the fragmentation of smart-city investments into siloed algorithmic pilots whose outputs do not compound because they are not designed as inputs for one another.

Design response: sequence the artefacts so that each earlier-stage output conditions the calibration space of downstream artefacts – operationally, the georeferenced inventory produced by DP1 supplies the spatial baseline for the failure-probability distributions in DP3; the normative luminance baselines formalised by DP2 define the safety floor within which the adaptive control in DP4 is free to optimise; and the maintenance prioritisation from DP3 feeds forward into operational scheduling under DP4. The resulting information governance chain has two consequences that make DP5 conceptually distinct from DP1–DP4. First, the marginal value of each artefact grows non-linearly with the presence of the others, because upstream artefacts reduce the calibration uncertainty of downstream artefacts – a form of complementarity that a purely additive view of smart-city investments cannot capture. Second, the chain reframes the governance object from “a set of tools” to “a structured flow of decision-relevant knowledge across the lifecycle”,

which is what municipal administrations need to govern.

Empirical anchor: cross-artefact information flows were observed and refined during the third deployment cycle described in [Section 2](#), in which the four artefacts were consolidated into a unified governance system.

Non-lighting transfer: the same lifecycle chaining logic is applicable to other civic infrastructure classes where the four generic phases (asset inventory → planning under regulation → predictive maintenance → adaptive operation) can be enumerated – for example, urban water networks, district heating networks or public transport infrastructure – provided that a lifecycle owner is identifiable and empowered to enforce the chaining architecturally.

From a DSR perspective, DP5 extends the design knowledge base by shifting the unit of design from the individual artefact to the inter-artefact information flow.

3. Discussion: synergistic impact, limitations and socio-technical considerations

3.1 The power of integration: the framework as an operational model

The integration of these tools constitutes, in effect, an operational Decision Support System (DSS) for public lighting governance – a modality of urban AI that bridges asset-level analytics and city-scale sustainability objectives ([Fistola & La Rocca, 2024](#)).

Joint adoption amplifies individual artefact benefits, addressing the smart-city “last mile” gap with an integrated, regulation-aware operational model.

Cross-country comparison of the deployments provides qualitative support for the transferability claim while also making its boundaries visible. In the Italian sites, mature municipal GIS layers and stable regulatory reference ([UNI 11248:2016](#)) allowed the full four-artefact chain to be exercised; in Spain and Chile, the GeoAI census artefact was the primary point of contact with municipal workflows, where detection accuracy (82–89% vs. 92.5% in Italy) reflected local variations in urban density, imagery resolution and ground-truth quality. Regulatory dependence is concentrated in the computational policy engine (DP2) and in the safety floor of the adaptive controller (DP4), both of which require re-encoding for jurisdictions with different national standards; the sensor-free maintenance model (DP3) and the geospatial census (DP1) are, by design, less regulation-dependent and therefore proved more directly portable across the three national contexts.

3.2 Socio-technical effects: governance responses and institutional adoption

Deploying AI in public infrastructure produces effects beyond technical performance, extending into institutional, organisational and social dimensions that the design principles in [Section 2.5](#) address directly. Challenges regarding algorithmic opacity were mitigated through an “explainability-by-design” approach, incorporating human-readable model cards and human-in-the-loop oversight to ensure auditable and accountable decision-making.

Experience from pilot trials suggests that long-term adoption is contingent upon identifying intra-organisational champions who can navigate the change-management processes required to embed data-driven insights into legacy planning and maintenance workflows.

In practice, the transition from pilot to routine operation required, in each site, three convergent enabling conditions (consistent with organisational scaling frameworks, e.g. [van Winden & van den Buuse, 2017](#)): (1) a designated lifecycle owner at operator side with cross-artefact authority, (2) explicit alignment of the artefact outputs with existing municipal procurement and reporting cycles, and (3) a documented human-in-the-loop escalation path for edge cases surfaced by the artefacts.

3.3 Limitations and outlook

Conducted within an industrial operator context, this study benefited from privileged access to deployment sites, operational datasets and longitudinal feedback across three geographies, but

also inherited specific boundaries: confidentiality on granular asset-level data and an emphasis on transferable design principles over exhaustive technical disclosure. The performance metrics and design principles should therefore be read as operationally grounded insights rather than universally generalisable benchmarks, and the framework as a practitioner-validated governance model rather than a prescriptive algorithmic specification.

While demonstrating robustness across pilot sites, the proposed framework possesses specific boundary conditions.

- (1) **Normative Encoding:** Some tools are tailored to specific regulatory environments. The compliance module is currently based on the Italian UNI 11248:2016 standard, and the adaptive control logic incorporates locally defined luminance thresholds. Application in other areas would require re-encoding of national or regional standards. However, the two-stage refinement architecture (DP2) is regulation-agnostic: re-encoding for other jurisdictions requires updating the fuzzy inference rules (C1/C2 thresholds) without modifying the underlying computational policy engine.
- (2) **Cultural and Institutional Factors:** The predictive maintenance model relies on probabilistic reasoning and model-based decision-making. Its adoption may be influenced by local institutional cultures and the willingness of operators to trust algorithmic outputs.
- (3) **Data Constraints:** The satellite-based inventory tool can detect the location and spectral characteristics of lighting assets but cannot yet infer structural attributes such as pole height or material. As such, it is not suitable for structural assessments or detailed asset condition evaluations.
- (4) **Institutional and geographic scope of the evidence:** Three of the four artefacts were exercised primarily in European municipalities, with one Latin American deployment; municipal contexts with substantially different institutional capacities, regulatory maturity, GIS/data readiness or infrastructure age may respond differently to the same framework. The transferability claims made for the design principles should therefore be read as hypotheses supported by cross-site operational experience, not as evidence of universal generalisability.
- (5) **Scalability and Integration:** Large-scale deployment requires integration with existing city infrastructure operators' workflows, data governance protocols and staff training programs. These factors may influence the pace and extent of adoption.

Future work extends in four complementary directions, all consistent with the boundary conditions identified above and already at exploratory or experimental stages within ongoing R&D activities.

On predictive maintenance (DP3), extension of the sensor-free logic to the structural condition assessment of infrastructure supports is under development. The approach draws on endogenous variables (material, geometry, location), exogenous factors known to affect service life, and, where available, field measurements, aiming to broaden the scope of prioritisation from failure risk to structural risk and to inform inspection-interval planning.

On design under regulation (DP2), the two-stage normative encoding approach is being explored for adjacent asset classes contributing to the overall lighting performance envelope. In particular, photometric characterisation of road-surface materials from imagery and geospatial information is under investigation as a way to feed richer input into the lighting design engine.

On lifecycle chaining beyond public lighting (DP5), transposition of the framework to other civic infrastructure classes is being examined starting from open-data climate risk indicators, which could support the identification of adaptation actions for critical urban infrastructure.

On information representation across the lifecycle (DP5), integration of the four artefacts within Building Information Modelling (BIM) environments and urban digital-twin platforms is under exploration as the natural informational substrate through which the inter-artefact chain described in [Section 2.5](#) can be operationalised at municipal scale.

Beyond these internally seeded directions, and consistent with the practitioner-research positioning of this study, we also see value in independent research on questions the present study cannot itself address – in particular, cross-platform comparative evaluation of the framework against alternative integrated smart-city solutions in matched deployments, and longitudinal cost-of-deployment measurement across broader geographic regions and varied municipal resource settings. The design principles derived in [Section 2.5](#) provide a conceptual scaffold for such extensions.

4. Conclusion

This practitioner-research case study provides deployment evidence that lifecycle-integrated AI governance for civic infrastructure is operationally feasible and institutionally adaptable across the three municipal contexts examined (Italy, Spain, Chile). The framework – spanning GeoAI census, computational policy encoding, probabilistic maintenance and adaptive edge control – produced the deployment metrics consolidated in [Table 2](#), obtained under real-world regulatory, privacy and institutional constraints and therefore not directly comparable to controlled experimental results.

The five transferable design principles derived from these deployments extend applicability beyond public lighting by articulating governance patterns – rather than domain-specific optimisations – that are architecturally relevant to other civic infrastructure domains facing similar data scarcity, regulatory complexity and institutional constraints.

By embedding urban informatics within existing infrastructure management workflows, this work advances SDG 7 and SDG 11, offering an operationally grounded pathway towards more sustainable and equitable urban services through accountable digital governance.

About the author

Sergio Gambacorta is an innovation manager and urban tech scholar-practitioner. His background spans more than 15 years of cross-domain experience within energy, telecommunications, civic technology, venture environments and public administration. Appointed in 2014 as an Independent Expert for the European Commission, he regularly advises on the evaluation of research and innovation programmes and smart governance policies. His track record includes multiple patents in urban informatics and digital civic infrastructure, alongside ongoing work as an academic author, invited guest lecturer and contributor to institutional white papers on infrastructure asset management and the digital transformation of public services.

Data availability

The underlying raw telemetry and operational datasets supporting the reported multi-city deployments are proprietary assets of Enel X S.r.l. and cannot be shared publicly due to confidentiality protocols and intellectual property protections. The overarching methodological architectures and design principles presented in this article are documented to allow independent conceptual evaluation.

Third-party material

Certain diagrams, architectural schematics and system figures included in this article are based on technical materials owned by Enel X S.r.l. Formal corporate authorisation has been granted by the copyright holder to publish these visual assets under the Creative Commons Attribution 4.0 International (CC BY 4.0) license. This permission is limited to the reproduction and dissemination of the figures and visual materials as included in the manuscript and solely for the purposes of publication of the article and does not extend to any underlying source material, technical documentation, databases, software, source code, models, know-how, methodologies, inventions and/or other proprietary assets of Enel X S.r.l. The

authorisation granted by Enel X S.r.l. is publication-specific and manuscript-specific and shall not constitute a standing authorisation for any future publication, reuse, adaptation or dissemination of the materials. No license, assignment, waiver or transfer of any patent rights, trade secrets, confidential information, copyright, software rights, database rights, industrial know-how or other intellectual property rights of Enel X S.r.l. is granted or implied. All such rights remain exclusively vested in Enel X S.r.l. Publication of the visual material included in the manuscript under the CC BY 4.0 licence shall not be construed as authorising access to, use of or reliance upon any proprietary technology, implementation details, algorithms, source code, methods or non-public technical information.

Declaration of AI use

AI assistance (Claude 4.6 Sonnet, Anthropic) was used for language editing and proofreading purposes only. All final editorial decisions and the responsibility for the manuscript's content remain entirely with the author.

Acknowledgments

The author thanks the Innovation and Business to Government team at Enel X. for their work in developing and operating the artefacts described in this study over the course of their deployment. The author also acknowledges the municipal administrations across the multi-city deployments, and thanks the industrial and academic partners whose technical contributions supported the calibration and implementation of specific artefacts described in this study.

References

- Albino, V., Berardi, U., & Dangelico, R. M. (2015). Smart cities: Definitions, dimensions, performance, and initiatives. *Journal of Urban Technology*, 22(1), 3–21. doi: [10.1080/10630732.2014.942092](https://doi.org/10.1080/10630732.2014.942092).
- Alvarez, R., Duarte, F., Frenchman, D., & Ratti, C. (2022). Sensing lights: The challenges of transforming street lights into an urban intelligence platform. *Journal of Urban Technology*, 29(4), 25–40. doi: [10.1080/10630732.2022.2082825](https://doi.org/10.1080/10630732.2022.2082825).
- Batty, M. (2012). Smart cities, big data. *Environment and Planning B: Planning and Design*, 39(2), 191–193. doi: [10.1068/b3902ed](https://doi.org/10.1068/b3902ed).
- European Commission (2019). The European green deal. Available from: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52019DC0640>
- Fistola, R., & La Rocca, R. A. (2024). From smart city to artificial intelligence city. Envisaging the future of urban planning. *TeMA – Journal of Land Use, Mobility and Environment*, 17(3), 411–421. doi: [10.6093/1970-9870/11081](https://doi.org/10.6093/1970-9870/11081).
- Gambacorta, S., & Becattini, G. (2025). *Computer-implemented system and method for optimizing energy consumption in public lighting*. (Italian Patent N. IT10202400001155, granted 30/01/2026). Enel X.
- Gambacorta, S., & Ferrara, G. (2025). *Method for calculation of the risk of failure in a lighting system*. (Italian Patent N.IT102023000013404, granted 07/01/2026; International application WO2025003931A1). Enel X.
- Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In F.-J. Kahlen, S. Flumerfelt, & A. Alves (Eds.), *Transdisciplinary Perspectives on Complex Systems* (pp. 85–113). Springer. doi: [10.1007/978-3-319-38756-7_4](https://doi.org/10.1007/978-3-319-38756-7_4).
- Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, 28(1), 75–105. doi: [10.2307/25148625](https://doi.org/10.2307/25148625).
- ISO 55000 (2014). *Asset management – overview, principles, and terminology*. International Organization for Standardization.
- Kitchin, R. (2013). The real-time city? Big data and smart urbanism. *GeoJournal*, 79(1), 1–14. doi: [10.1007/s10708-013-9516-8](https://doi.org/10.1007/s10708-013-9516-8).

- Kitchin, R. (2018). Reframing, reimagining, and remaking smart cities. In C. Coletta, L. Evans, L. Heaphy, & R. Kitchin (Eds.), *Creating Smart Cities* (pp. 219–230). Routledge. doi: [10.4324/9781351182409-17](https://doi.org/10.4324/9781351182409-17).
- Kitchin, R., Cardullo, P., & Di Felicianantonio, C. (2019). Citizenship, justice, and the right to the smart city. In R. Kitchin, P. Cardullo, & C. Di Felicianantonio (Eds.), *The Right to the Smart City* (pp. 1–24). Emerald Publishing. doi: [10.1108/978-1-78769-139-120191001](https://doi.org/10.1108/978-1-78769-139-120191001).
- Lafioune, N., Poirier, E. A., & St-Jacques, M. (2024). Managing urban infrastructure assets in the digital era: Challenges of municipal digital transformation. *Digital Transformation and Society*, 3(1), 3–22. doi: [10.1108/DTS-02-2023-0010](https://doi.org/10.1108/DTS-02-2023-0010).
- Levin, N., Kyba, C. C., Zhang, Q., Sánchez de Miguel, A., Román, M. O., Li, X., . . . Elvidge, C. D. (2020). Remote sensing of night lights: A review and an outlook for the future. *Remote Sensing of Environment*, 237, 111443. doi: [10.1016/j.rse.2019.111443](https://doi.org/10.1016/j.rse.2019.111443).
- Li, Z., Wang, Y., Zhang, N., Zhang, Y., Zhao, Z., Xu, D., . . . Gao, Y. (2022). Deep learning-based object detection techniques for remote sensing images: A survey. *Remote Sensing*, 14(10), 2385. doi: [10.3390/rs14102385](https://doi.org/10.3390/rs14102385).
- Mortaheb, R., & Jankowski, P. (2023). Smart city re-imagined: City planning and GeoAI in the age of big data. *Journal of Urban Management*, 12(1), 4–15. doi: [10.1016/j.jum.2022.08.001](https://doi.org/10.1016/j.jum.2022.08.001).
- Ożadowicz, A., & Grela, J. (2017). Energy saving in the street lighting control system — a new approach based on the EN-15232 standard. *Energy Efficiency*, 10(3), 563–576. doi: [10.1007/s12053-016-9476-1](https://doi.org/10.1007/s12053-016-9476-1).
- Regona, M., Yigitcanlar, T., Hon, C., & Teo, M. (2024). Artificial intelligence and sustainable development goals: Systematic literature review of the construction industry. *Sustainable Cities and Society*, 102, 105499. doi: [10.1016/j.scs.2024.105499](https://doi.org/10.1016/j.scs.2024.105499).
- Shi, W., Goodchild, M. F., Kwan, M. P., Zhang, A., & Batty, M. (2021). *Urban informatics*. Springer. doi: [10.1007/978-981-15-8983-6](https://doi.org/10.1007/978-981-15-8983-6).
- Shi, W., Goodchild, M. F., Batty, M., Kwan, M.-P., & Zhang, A. (2022). Prospective for urban informatics. *Urban Informatics*, 1, 2. doi: [10.1007/s44212-022-00006-0](https://doi.org/10.1007/s44212-022-00006-0).
- Team Nachlichter, Tegeler, A., Marz, A., Gokus, A., Hänel, A., Rienow, A., Ruby, A., . . . Altıntaş, Y. . Ö. (2025). Citizen science illuminates the nature of city lights. *Nature Cities*, 2(6), 496–505. doi: [10.1038/s44284-025-00239-5](https://doi.org/10.1038/s44284-025-00239-5).
- UNI 11248:2016 (2016). *Road lighting – selection of lighting classes*. Ente Nazionale Italiano di Unificazione.
- van Winden, W., & van den Buuse, D. (2017). Smart city pilot projects: Exploring the dimensions and conditions of scaling up. *Journal of Urban Technology*, 24(4), 51–72. doi: [10.1080/10630732.2017.1348884](https://doi.org/10.1080/10630732.2017.1348884).
- Weber, P., Medina-Oliva, G., Simon, C., & Iung, B. (2012). Overview on Bayesian networks applications for dependability, risk analysis, and maintenance areas. *Engineering Applications of Artificial Intelligence*, 25(4), 671–682. doi: [10.1016/j.engappai.2010.06.002](https://doi.org/10.1016/j.engappai.2010.06.002).
- Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353. doi: [10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X).
- Zanella, A., Bui, N., Castellani, A., Vangelista, L., & Zorzi, M. (2014). Internet of things for smart cities. *IEEE Internet of Things Journal*, 1(1), 22–32. doi: [10.1109/JIOT.2014.2306328](https://doi.org/10.1109/JIOT.2014.2306328).
- Zhu, X. X., Tuia, D., Mou, L., Xia, G. -S., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep learning in remote sensing: A comprehensive review and list of resources. *IEEE Geoscience and Remote Sensing Magazine*, 5(4), 8–36. doi: [10.1109/MGRS.2017.2762307](https://doi.org/10.1109/MGRS.2017.2762307).

Corresponding author

Sergio Gambacorta can be contacted at: sergio.gambacorta@gmail.com