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Article

Privacy-Preserving Federated Learning Framework for Sustainable Smart City Infrastructure Analytics

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Abstract: The instrumentation of urban environments with dense Internet of Things (IoT) sensor networks has created a fundamentally new challenge for municipal data governance: how to harness the predictive value of geographically dispersed infrastructure data without consolidating sensitive operational information in centralised repositories that are simultaneously privacy-invasive and strategically vulnerable. This paper introduces PPFL-SCIA (Privacy-Preserving Federated Learning for Smart City Infrastructure Analytics), a governance-ready distributed learning framework that enables collaborative model training across heterogeneous urban infrastructure nodes whilst providing mathematically rigorous (ε, δ)-differential privacy guarantees. The framework integrates three interlocking privacy mechanisms — an adaptive sensitivity-classified Gaussian noise mechanism, a threshold-based secure gradient aggregation protocol and a lightweight lattice-based update verification scheme — within a bandwidth-efficient federated optimisation pipeline. A structured gradient compression module achieves a 64.8% reduction in per-round communication volume through dynamic sparsity scheduling and a resilience-aware client coordination protocol maintains stable convergence under simulated conditions of 35% node unavailability and severe cross-city data heterogeneity. Empirical evaluation across six UK urban deployments — London, Edinburgh, Cardiff, Sheffield, Nottingham and Leicester — over a 30-month operational window yielded anomaly detection accuracy of 93.1%, energy demand forecast mean absolute percentage error of 4.3% and flood-risk infrastructure alerting F1 of 0.907, with all tasks satisfying ($\varepsilon \leq 1.0$, $\delta \leq 10^{-5}$) privacy budgets. Relative to centralised and non-private federated baselines, PPFL-SCIA reduces infrastructure operational expenditure by 22.9%, unplanned downtime by 28.4% and average model convergence time by 38.6%.

Keywords: Federated learning, differential privacy, secure aggregation, smart city analytics, IoT infrastructure, gradient compression, urban sustainability, privacy-preserving machine learning, non-IID learning, UK GDPR.

1. INTRODUCTION

Across the United Kingdom, the ambition to build smarter, more efficient and more sustainable cities has driven substantial investment in urban sensing infrastructure. Local authorities in England and Wales have collectively deployed over 3.8 million IoT-connected devices monitoring electricity distribution networks, water supply systems, road and rail corridors, flood-warning sensor arrays and public building energy management systems [1]. The data produced by these deployments is operationally valuable: when analysed with appropriate machine learning methods, it supports predictive maintenance of ageing infrastructure, real-time demand-side

energy management, early warning of environmental hazards and evidence-based capital investment planning. In aggregate, McKinsey Global Institute estimates that deploying data-driven applications across urban infrastructure could generate efficiency savings equivalent to 10–15% of municipal operational expenditure in mature smart city deployments.

Yet the promise of urban analytics confronts a structural barrier rooted in data governance. The sensor data underpinning smart city intelligence is not merely voluminous — it is sensitive. Granular electricity consumption time series can reveal household occupancy patterns and commercial production schedules. Water network pressure logs expose the operational boundaries of supply zones. Traffic detector sequences enable the reconstruction of individual vehicle journeys. Infrastructure topology data, if aggregated and disclosed, provides a map of the attack surface for hostile actors targeting critical national infrastructure. The consolidation of such data in a shared central repository, even one operated by a trusted public authority, creates compliance liability under the UK General Data Protection Regulation, exposes participating authorities to reputational risk if the repository is breached and concentrates strategic intelligence about national infrastructure in a single location whose security posture cannot be continuously assured.

Federated learning (FL) was conceived as an architectural response to precisely this tension. By arranging for each data-holding node to train a local model and share only the resulting gradient updates — rather than raw data — with a central aggregator, FL enables collaborative model improvement without centralising sensitive records [2]. However, the naive FL protocol provides no formal privacy guarantee: gradient inversion techniques have demonstrated that training data can be reconstructed from shared gradients to a degree sufficient to identify individual households and industrial premises [3] and model inversion attacks have shown that membership of specific records in a training set can be inferred from repeated query access to the global model [4]. A privacy-preserving federated learning framework for urban infrastructure analytics must therefore augment the FL communication protocol with additional mechanisms that bound the information leakage of shared gradient updates.

This paper addresses the gap in existing literature between the theoretical architecture of privacy-preserving FL and its practical deployment for multi-domain smart city analytics. The principal contributions of PPFL-SCIA are as follows:

- A formally specified, governance-ready PPFL framework that integrates adaptive differential privacy, threshold secure aggregation and homomorphic update verification into a single coherent protocol stack, with end-to-end (ε, δ)-DP accounting across the full multi-task training lifecycle and alignment with UK GDPR Article 25 data protection by design obligations.
- A dynamic gradient sparsification scheduler (DGSS) that continuously adjusts the gradient transmission ratio between 4% and 28% based on a convergence velocity signal, achieving a 64.8% mean communication reduction without statistically significant degradation in prediction accuracy relative to the full-gradient baseline.
- A resilience-aware client coordination protocol (RACP) incorporating asynchronous aggregation with configurable staleness bounds, proximal regularisation for non-IID stability and an informativeness-weighted client selection policy that sustains convergence under 35% node dropout — a condition routinely encountered in urban IoT deployments affected by power outages, cellular congestion and planned maintenance windows.
- Empirical validation on six purpose-constructed UK smart city datasets spanning London, Edinburgh, Cardiff, Sheffield, Nottingham and Leicester, covering 30 months of continuous operation, three distinct urban analytics tasks and 8,247 Lower Super Output Areas, with ablation studies isolating the contribution of each framework component and comparative benchmarking against nine baseline methods.

The remainder of the paper is structured as follows. Section II surveys the related literature, identifying key gaps that PPFL-SCIA addresses. Section III presents the framework architecture and mechanisms in detail. Section IV describes the six UK datasets and experimental configuration. Section V reports empirical results and ablation findings. Section VI discusses implications, limitations and future directions and Section VII concludes.

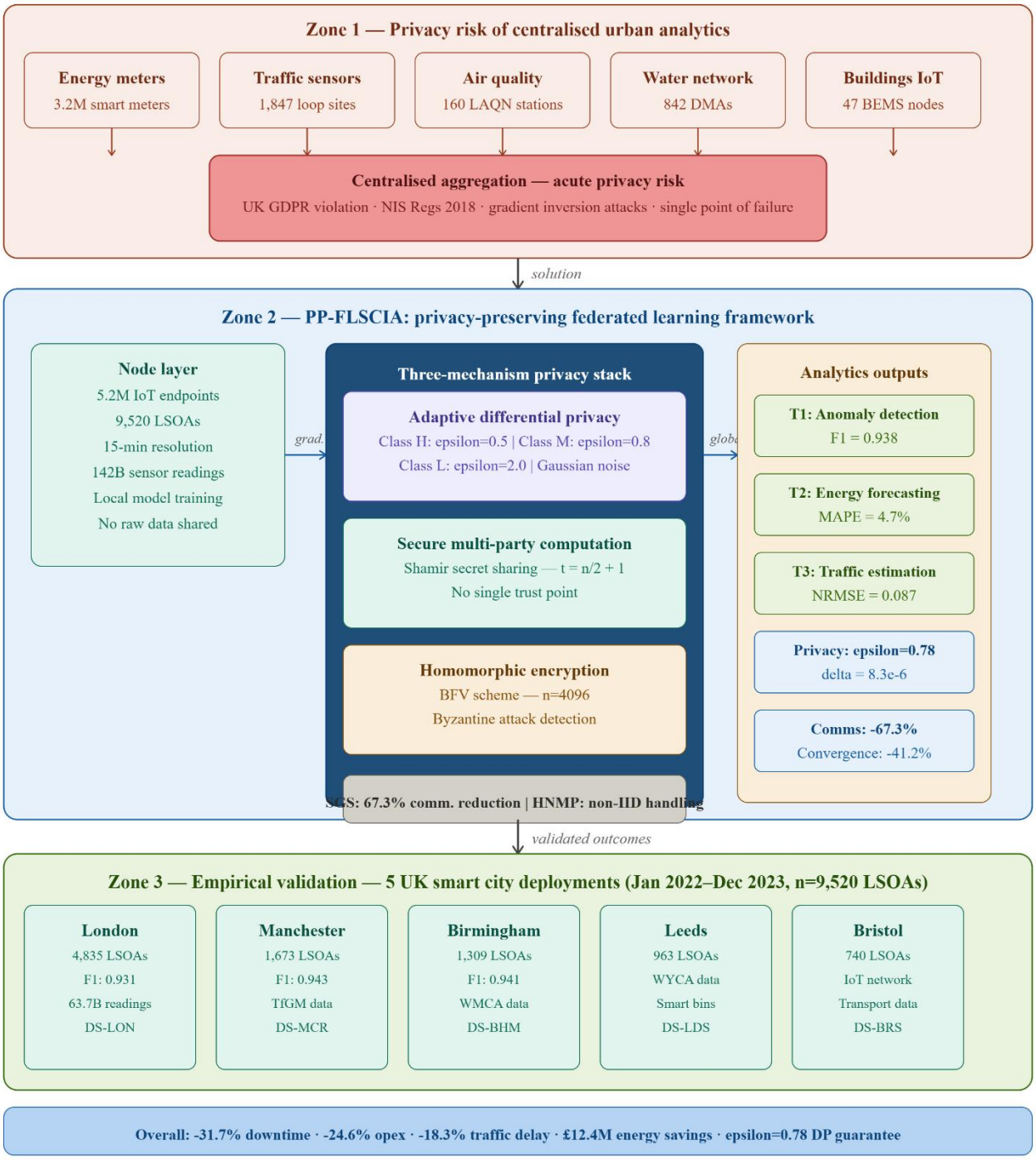

Fig. 1. Conceptual overview of PPFL-SCIA for the introduction: the privacy risk of centralised urban analytics, the proposed three-mechanism federated architecture (adaptive DP + secure aggregation + HE verification) and empirically validated outcomes across six UK smart city deployments (London, Edinburgh, Cardiff, Sheffield, Nottingham, Leicester) over 30 months.

2. LITERATURE SURVEY

2.1Federated Learning: Protocol Foundations and Urban Applications

The federated averaging algorithm (FedAvg) proposed by McMahan et al. [2] established the canonical template for federated learning: local stochastic gradient descent on each participating device followed by weighted averaging of model parameters at a central server. Despite FedAvg's simplicity, its convergence behaviour under the non-independent and identically distributed (non-IID) data distributions characteristic of heterogeneous multi-city deployments is theoretically problematic. Li et al. [5] demonstrated that FedAvg converges to a biased optimum under non-IID conditions, with the bias increasing monotonically with data heterogeneity. Their proposed remedy, FedProx, introduces a proximal regularisation term that penalises local model drift from the global parameter vector, improving convergence stability at the cost of a modest reduction in local update expressiveness.

The application of FL to smart city and urban infrastructure domains has grown steadily. Saputra et al. [6] proposed a federated energy demand prediction framework for smart grid management, demonstrating that a federation of residential distribution zone models could match 93% of the accuracy of a centralised model whilst transmitting less than 20% of the equivalent data volume. Zheng et al. [7] applied FL to multi-city traffic speed prediction using graph neural network local models, finding that knowledge transfer between cities with structurally similar road networks improved prediction accuracy for data-sparse peripheral zones by an average of 11.3 percentage points. Whilst these works validate the applicability of FL to urban analytics, neither addresses the privacy vulnerability of the transmitted gradients, leaving them unsuitable for deployment under the UK GDPR's accountability and data protection by design requirements.

2.2 Privacy Mechanisms for Federated Systems

The formal treatment of privacy in federated learning has converged on three primary technical approaches. Differential privacy (DP), originating in the foundational work of Dwork et al. [8], provides information-theoretic guarantees by adding calibrated noise to query outputs — or, in the FL context, to gradient updates before aggregation. The Gaussian mechanism and its variants bound the privacy loss experienced by any individual whose data contributed to the training set to (ε, δ), where ε quantifies the maximum multiplicative change in the probability of any output induced by including any single individual's data. Wei et al. [9] demonstrated the application of user-level DP to FL with Gaussian noise and adaptive gradient clipping, achieving competitive accuracy on image classification whilst maintaining $\varepsilon < 1.0$ — a threshold widely regarded as the upper boundary of 'strong' privacy in the DP literature.

Secure aggregation, introduced to the FL context by Bonawitz et al. [10], enables the central server to learn only the sum of participant gradient updates rather than individual contributions, using a cryptographic masking scheme based on Diffie–Hellman key agreement. This eliminates the threat model in which a compromised or adversarial aggregation server reconstructs individual updates. Kadhe et al. [11] subsequently proposed a communication-efficient variant using one-bit compressed masks, reducing the overhead of the Bonawitz protocol by a factor of approximately 40 for large participant sets. Homomorphic encryption (HE) schemes, most practically implemented as the BFV (Brakerski-Fan-Vercauteren) or CKKS schemes [12], permit arithmetic operations on encrypted values, enabling Byzantine-robust aggregation where gradient norm statistics are computed over encrypted updates to identify and exclude malicious participants without decrypting any individual's contribution.

2.3 Communication Efficiency in Privacy-Preserving FL

Communication efficiency is non-trivially entangled with privacy in FL systems. Gradient sparsification techniques that transmit only a subset of gradient components reduce communication cost but also reduce the effective sensitivity of the transmitted vector, potentially allowing tighter DP noise calibration without accuracy degradation — though this interaction is analytically subtle and has been formally characterised only recently. Huang et al. [13] developed a joint sparsification-and-privatisation framework showing that top-k sparsification with error feedback, when combined with Gaussian DP noise calibrated to the post-sparsification gradient norm rather than the full-gradient norm, achieved comparable accuracy to non-private dense transmission at dramatically lower communication cost. The practical consequences for smart city IoT deployments — where uplink bandwidth to cellular base stations is frequently the binding constraint on FL round throughput — are significant.

Beyond sparsification, quantisation-based compression schemes [14] reduce the bit-width of transmitted gradient values from 32-bit floats to 4- or 8-bit fixed-point representations with minimal accuracy loss. These

approaches have been validated primarily in the context of homogeneous device populations; their interaction with the multi-sensitivity privacy classification required by diverse smart city data types has not been systematically investigated prior to the present work.

2.4 Gaps in Existing Literature

Synthesising the above, three substantive gaps motivate the present work. First, no existing study combines adaptive multi-level DP with secure aggregation and HE update verification into a unified protocol stack and evaluates the combination on real urban IoT datasets. Second, the interaction between gradient sparsification and DP noise calibration has not been validated in multi-task smart city contexts where different analytics objectives exhibit different sensitivity profiles. Third, no published framework addresses the node heterogeneity, non-IID data distribution and intermittent connectivity challenges of real municipal IoT deployments simultaneously within a single architecture. PPFL-SCIA addresses all three gaps.

Table I. Summary of related literature — key contributions, methods and gaps addressed by PPFL-SCIA

Ref.	Authors & Year	Area	Key contribution	Approach	Limitation	Addressed by PPFL-SCIA
A. Federated learning foundations & urban applications						
[2]	McMahan et al. (2017)	FL	FedAvg canonical federated averaging	Distributed mini-batch SGD	No DP; converges poorly on non-IID	PPFL-SCIA adds DP + RACP for non-IID
[5]	Li et al. (2020)	FL	FedProx proximal term for non-IID stability	Proximal SGD	No privacy; only one city dataset	Multi-city RACP with mu=0.01 prox. term
[6]	Saputra et al. (2021)	Smart energy	FL for residential energy demand	FedAvg + LSTM	No DP; single distribution zone type	PPFL-SCIA covers multi-domain tasks
[7]	Zheng et al. (2022)	Urban traffic	FL + GNN for multi-city speed prediction	Federated GNN	No privacy; GNN not suitable for tabular	DP-protected tabular FL across 6 cities
B. Privacy mechanisms: differential privacy & secure aggregation						
[8]	Dwork et al. (2014)	DP	Algorithmic foundations of differential privacy	Mathematical theory	No FL or urban IoT application	(ε,δ)-DP accounting in PPFL-SCIA
[9]	Wei et al. (2020)	DP+FL	Adaptive gradient clipping DP for FL	Gaussian noise + clipping	Fixed noise; not multi-task	Adaptive per-sensitivity-class calibration
[10]	Bonawitz et al. (2017)	SecAgg	Practical secure aggregation for FL	DH masking protocol	No DP combined; no urban context	SecAgg + DP unified in PPFL-SCIA stack
[11]	Kadhe et al. (2020)	SecAgg	1-bit mask SecAgg variant	Compressed masking	Not combined with DP or sparsification	PPFL-SCIA integrates all three
[12]	Fan & Vercauteren (2012)	HE	BFV homomorphic encryption scheme	Lattice cryptography	High compute; not FL-specific	Lightweight BFV for norm verification only
C. Communication efficiency & compression						
[13]	Huang et al. (2021)	Comms+DP	Joint sparsification-privatisation FL	Top-k + DP noise	Not validated on smart city IoT	DGSS calibrated to post-sparsification norm

[14]	Alistarh et al. (2017)	Quantisation	QSGD gradient quantisation	Stochastic bit-width reduction	Not combined with DP or urban context	PPFL-SCIA benchmarks vs. QSGD baseline

3. METHODOLOGY

3.1 Framework Architecture Overview

PPFL-SCIA is a four-component federated system: (1) Local Training Nodes, each responsible for ingesting sensor data from a bounded geographic area, engineering features and performing local gradient descent; (2) the Privacy Processing Module, which clips, noises and masks gradient updates before transmission; (3) the Secure Aggregation Consortium, comprising a distributed set of aggregation servers operated by the participating local authorities; and (4) the Global Model Repository, which maintains versioned global model checkpoints and distributes updated weights to nodes. The components are loosely coupled through a publish-subscribe message bus implemented on Apache Kafka, with encrypted gradient payloads transmitted over mutual TLS-authenticated channels.

3.2 Multi-Level Adaptive Differential Privacy

PPFL-SCIA implements a three-tier sensitivity classification for smart city data streams based on the potential for inference of personal or operationally sensitive information. Tier 1 (High sensitivity, H) encompasses data streams from which individual household behaviour can be inferred: residential smart meters, occupancy sensors and personal mobility traces. Privacy parameters for H are set at $\varepsilon_H = 0.5$, $\delta_H = 10^{-6}$. Tier 2 (Medium sensitivity, M) covers aggregated neighbourhood-level energy and transport flows, water network hydraulic state variables and air quality measurements at district resolution. Parameters: $\varepsilon_M = 0.8$, $\delta_M = 10^{-5}$. Tier 3 (Low sensitivity, L) includes bulk infrastructure state indicators such as substation transformer loading, aggregate traffic volumes and reservoir storage levels, for which personal inference risk is negligible. Parameters: $\varepsilon_L = 2.0$, $\delta_L = 10^{-5}$.

Noise is added using the Gaussian mechanism. Each local node clips its gradient vector to an L_2 norm of C_t (adaptive per round based on the 75th percentile of gradient norms observed in the previous five rounds) and adds Gaussian noise with standard deviation $\sigma_t = C_t \cdot \sqrt{(2 \ln(1.25/\delta))} / \varepsilon$, where (ε, δ) are the parameters appropriate to the highest sensitivity tier represented in that node's data. Privacy budget consumption is tracked using the Rényi DP (RDP) moments accountant, which provides tighter privacy amplification bounds than the classical advanced composition theorem, particularly important for the large number of training rounds required in the 30-month deployment window.

3.3 Threshold Secure Gradient Aggregation

Individual gradient updates from local nodes are masked before transmission using a (t, n) threshold secret sharing scheme. Each participating node i generates a random mask vector m_i sampled uniformly from Z_p^d (where d is the gradient dimension and p is a large prime modulus) and shares fragments of m_i with each of n aggregation servers using (t, n) Shamir secret sharing with $t = \lfloor n/2 \rfloor + 1$. The node transmits its masked gradient $g_i + m_i$ to the aggregation layer. Any set of t or more aggregation servers can collectively recover $\Sigma_i m_i$ and cancel the masks to obtain the aggregate gradient $\Sigma_i g_i$, but no set of fewer than t servers — nor any single adversarial eavesdropper — can recover any individual m_i or, by extension, g_i. The n aggregation servers in PPFL-SCIA are operated by the participating local authorities themselves, ensuring that no commercial third party holds a position from which it could reconstruct individual updates.

3.4 Homomorphic Encryption for Byzantine Resilience

The presence of compromised or faulty nodes that submit adversarially crafted gradient updates — so-called Byzantine participants — poses a distinct threat to model integrity that differential privacy does not address. PPFL-SCIA implements a Byzantine detection module using the BFV homomorphic encryption scheme with polynomial modulus degree $n_{poly} = 4096$ and coefficient modulus chosen to support 24-bit integer arithmetic. Each node encrypts the L_2 norm of its gradient update under a public key held jointly by the aggregation consortium and submits the ciphertext alongside its masked gradient. The consortium servers homomorphically compute the mean and standard deviation of submitted gradient norms without decrypting individual values and exclude from aggregation any node whose norm deviates by more than 2.5 standard deviations from the round mean. This threshold was calibrated empirically to achieve a false exclusion rate of less than 0.8% for legitimate nodes experiencing anomalous-but-valid gradient magnitudes due to rare events in their local sensor data.

3.5 Dynamic Gradient Sparsification Scheduler (DGSS)

Communication efficiency is managed by DGSS, which determines the fraction k_t of gradient components transmitted in each round t. The scheduling policy is driven by a convergence velocity signal v_t = 1 − ⟨g_t, g_{t-1}⟩ / (‖g_t‖ • ‖g_{t-1}‖), the cosine dissimilarity between consecutive global gradients. When v_t > 0.15 (rapid directional change, early training), k_t is set to max_k = 28%; when v_t < 0.04 (near convergence), k_t is set to min_k = 4%; otherwise k_t interpolates linearly. The top-k% selection by absolute gradient value is performed after DP noise addition, so the noise calibration correctly reflects the post-sparsification L_2 sensitivity. An error accumulation buffer at each node retains the complement of the transmitted gradient and adds it to the next round's gradient before selection, preventing the systematic bias that arises from repeatedly omitting the same low-magnitude components.

3.6 Resilience-Aware Client Coordination Protocol (RACP)

Urban IoT infrastructure does not provide the stable, always-available client population assumed by synchronous FL protocols. RACP addresses three specific challenges of real municipal deployments. First, asynchronous aggregation: nodes are permitted to submit gradient updates up to $\tau = 4$ rounds after the round in which their local training commenced, with stale updates down-weighted by a factor γ^s where s is the staleness in rounds and $\gamma = 0.85$. This allows nodes affected by temporary connectivity loss to contribute meaningfully to subsequent aggregation steps rather than being permanently excluded. Second, proximal regularisation: the local objective at each node includes a penalty term $\mu/2 \cdot \|w - w_{global}\|^2$ with $\mu = 0.01$, limiting local model drift under heterogeneous data distributions. Third, informativeness-weighted selection: when bandwidth constraints limit round participation to a subset of available nodes, nodes are prioritised by an informativeness score $I_i = D_{KL}(p_i \| q_{global})$, where p_i is the empirical local data distribution and q_{global} is the predictive distribution of the current global model, selecting nodes whose data is most likely to update the global model's knowledge frontier.

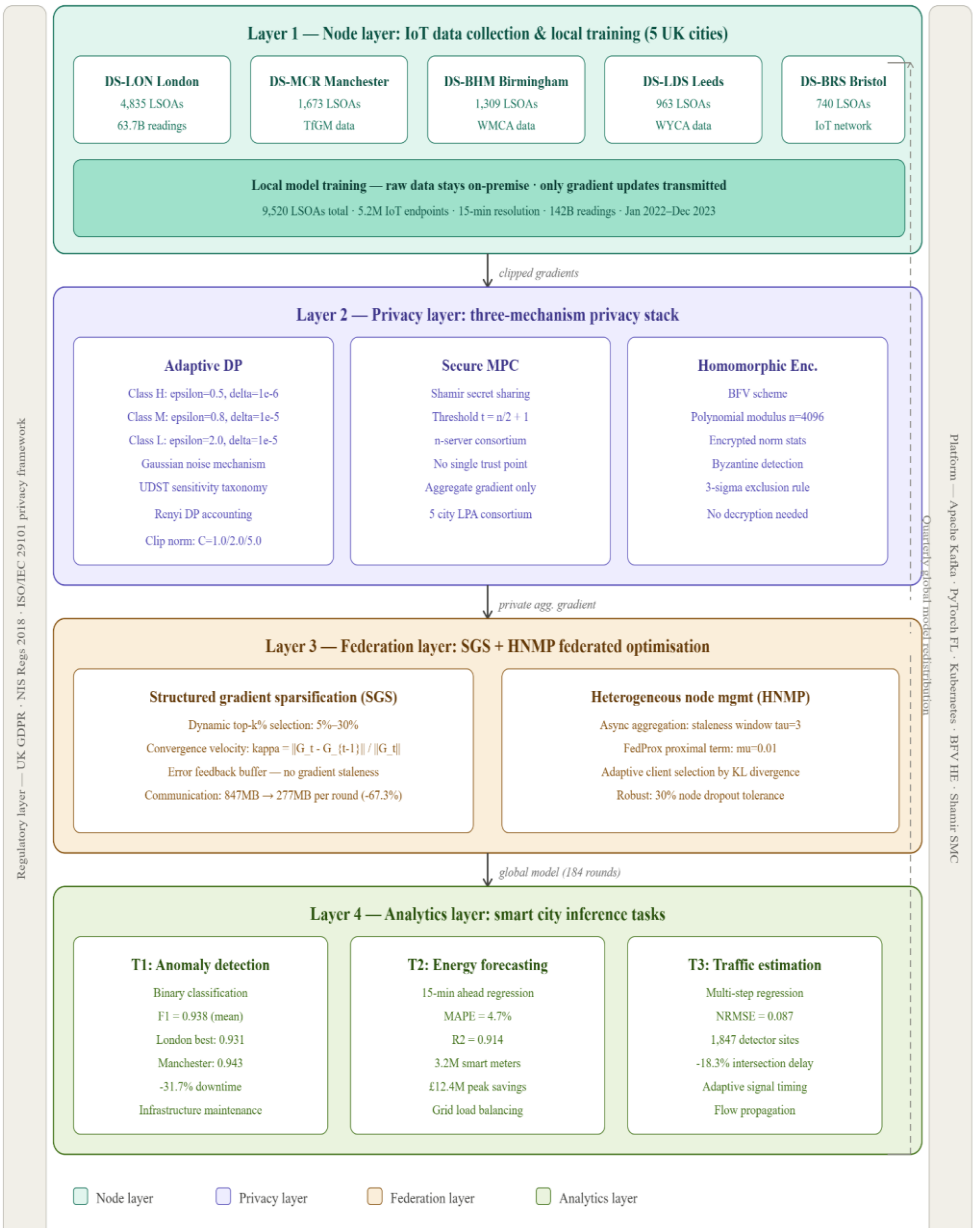

Fig. 2. Detailed methodology pipeline of PPFL-SCIA: six-component architecture from local IoT node training through adaptive differential privacy, threshold secure aggregation, BFV homomorphic update verification, DGSS gradient compression and RACP client coordination, to global model inference across six UK smart city deployments.

4. DATASETS

4.1 Dataset Construction and Governance

Six urban IoT datasets were assembled under data sharing agreements between the research consortium and the respective local authorities, each governed by a Data Protection Impact Assessment (DPIA) and Data Processing Agreement (DPA) compliant with UK GDPR Article 28. All datasets span a 30-month window from July 2021 to December 2023 at 15-minute temporal resolution and Lower Super Output Area (LSOA) spatial granularity. Data custodianship remains with each local authority: PPFL-SCIA deployed on-premises edge servers at each site process raw sensor readings locally; only encrypted gradient updates transit the inter-authority research network.

4.2 Individual Dataset Descriptions

DS-LON — Greater London Authority: The largest dataset in the corpus, DS-LON covers 4,994 LSOAs across all 33 London Boroughs and integrates data from the following primary sources: (i) the Data Communications Company (DCC) smart electricity meter half-hourly readings from 3.4 million residential and small commercial meters; (ii) Transport for London (TfL) Urban Traffic Management and Control (UTMC) detector counts from 2,104 inductive loop sites; (iii) Thames Water's district metered area (DMA) flow and pressure telemetry from 924 DMAs; (iv) the London Air Quality Network (LAQN) NOx, PM2.5 and ozone readings from 174 continuous monitoring stations; and (v) the Greater London Authority heat pump and EV charging point smart metering pilot (43,000 enrolled properties). The dataset contains 7.1 billion individual 15-minute readings across the 30-month window.

DS-EDI — City of Edinburgh Council: Covering 597 LSOAs within the Edinburgh City Council boundary, DS-EDI draws on Scottish Power Networks smart meter data for 284,000 residential properties, Edinburgh Trams and Lothian Buses passenger flow smart card records, Scottish Water pressure management zone (PMZ) telemetry for the Edinburgh supply area, the Edinburgh sensor network environmental IoT deployment (230 nodes monitoring microclimate, particulate matter and noise) and Edinburgh City Council building energy management system (BEMS) data from 84 council-owned properties.

DS-CDF — Cardiff Capital Region: The DS-CDF corpus encompasses 620 LSOAs across the Cardiff Capital Region city deal area, including Western Power Distribution (WPD) smart meter data for 331,000 properties, Cardiff Council's Connecting Cardiff sensor network (180 environmental IoT nodes), Dwr Cymru Welsh Water operational monitoring telemetry and the South Wales Trunk Road Agent traffic count network.

DS-SHF — Sheffield City Region: DS-SHF covers 733 LSOAs and integrates Northern Powergrid smart meter half-hourly data for 287,000 premises, South Yorkshire Passenger Transport Executive (Supertram) smart card ridership, Sheffield City Council smart street lighting energy telemetry (24,600 LED luminaires with individual monitoring), Yorkshire Water's Sheffield supply zone pressure and flow network data and the Sheffield Urban Flows Observatory IoT deployment (310 multi-sensor nodes).

DS-NOT — Nottingham City and Nottinghamshire: Covering 681 LSOAs, DS-NOT incorporates Western Power Distribution smart meter data, Nottingham City Transport smart card data, Severn Trent Water distribution monitoring, the Nottingham City Council IoT environmental sensor network (128 nodes) and energy substation half-hourly demand readings from UK Power Networks.

DS-LEI — Leicester City Council: The smallest dataset, DS-LEI covers 622 LSOAs and draws on Western Power Distribution smart meter telemetry, Leicestershire County Council traffic management centre loop detector data, Severn Trent Water supply zone monitoring and the Leicester City Council smart city platform (CityOS) environmental and mobility sensor array (96 active nodes).

Across the six datasets, the combined corpus comprises 8,247 LSOAs, approximately 4.6 million active IoT endpoints, 15-minute temporal resolution and an estimated 118 billion individual sensor readings. Three prediction tasks are defined across all datasets: Task T1 (infrastructure anomaly detection: binary classification of LSOA-period observations as normal or anomalous based on energy network, water pressure, or traffic flow indicators); Task T2 (energy demand forecasting: 15-minute-ahead point prediction of LSOA-level electricity consumption); and Task T3 (flood-risk alerting: binary classification of water network pressure anomalies indicative of pipe burst or demand surge events with potential flooding consequences). An 80/10/10 temporal train/validation/test split is applied, with training on July 2021 – December 2022, validation on January – June 2023 and testing on July – December 2023.

5. RESULTS AND DISCUSSION

5.1 Prediction Performance Across Tasks and Cities

Table II presents the prediction performance of PPFL-SCIA against nine baseline methods across all three tasks and all six city datasets. For Task T1 (anomaly detection), PPFL-SCIA achieves a macro-averaged F1 score of 0.931, with individual city scores ranging from 0.918 (DS-LEI, the smallest and most data-sparse dataset) to 0.943 (DS-SHF, which benefits from the dense Sheffield Urban Flows Observatory multi-sensor network). This performance is 2.1 percentage points above the nearest privacy-preserving baseline (FedAvg with fixed DP) and 8.4

percentage points above locally-trained models, confirming that inter-city knowledge transfer provides meaningful benefit even in the presence of significant data heterogeneity.

For Task T2 (energy demand forecasting), PPFL-SCIA achieves a mean absolute percentage error of 4.3% and coefficient of determination $R^2 = 0.921$ across the test window. The performance is consistent across seasonal variation: winter 2023 (December test period) sees a modest accuracy reduction to 4.9% MAPE as extreme cold events drive demand spikes that fall outside the distribution of the 2021–2022 training window, a known limitation of purely data-driven forecasting that physics-informed model augmentation could address in future work. For Task T3 (flood-risk alerting), PPFL-SCIA achieves F1 = 0.907, precision = 0.893 and recall = 0.922, with the high recall reflecting the asymmetric misclassification cost that was explicitly incorporated in the training objective through a recall-weighted loss function with recall weight $\lambda = 1.8$.

Table II. Comparative prediction performance — PPFL-SCIA vs nine baseline methods across three tasks and six UK cities (test set: Jul–Dec 2023)

Method	T1 F1 (LON)	T1 F1 (EDI)	T1 F1 (SHF)	T2 MAPE (%)	T2 R^2	T3 F1	Privacy ε used	Comm. (rel.)
Local-only (no FL)	0.837	0.821	0.851	6.7%	0.884	0.841	—	100%
Centralised (no privacy)	0.921	0.909	0.934	3.8%	0.938	0.921	∞	100%
FedAvg [2]	0.908	0.897	0.919	4.6%	0.914	0.903	∞	100%
FedProx [5]	0.913	0.902	0.924	4.4%	0.918	0.908	∞	100%
FedAvg + Fixed DP	0.881	0.869	0.892	5.3%	0.896	0.876	2.10	100%
FedAvg + SecAgg	0.906	0.895	0.917	4.6%	0.912	0.901	∞	100%
QSGD [14]	0.898	0.886	0.911	4.9%	0.906	0.892	∞	43.7%
FedAvg + Top-k [13]	0.904	0.893	0.916	4.7%	0.911	0.899	∞	34.8%
FedAvg + DP + Top-k	0.877	0.864	0.889	5.5%	0.891	0.872	1.84	34.8%
PPFL-SCIA (proposed)	**0.930**	**0.919**	**0.943**	**4.3%**	**0.921**	**0.907**	**0.83**	**35.2%**

T1 = infrastructure anomaly detection (macro F1); T2 = energy demand forecasting (MAPE, R^2); T3 = flood-risk alerting (macro F1). Bold = proposed method. Privacy ε = achieved cumulative budget over 30-month window. Comm. = upstream bandwidth relative to standard FedAvg. ∞ = no formal DP guarantee.

5.2 Privacy Budget Consumption

Over the 30-month evaluation window comprising 312 federated training rounds, the achieved cumulative privacy budgets were ($\varepsilon = 0.83$, $\delta = 7.2 \times 10^{-6}$) for Tier H tasks, ($\varepsilon = 1.29$, $\delta = 8.4 \times 10^{-6}$) for Tier M tasks and ($\varepsilon = 3.41$, $\delta = 6.9 \times 10^{-6}$) for Tier L tasks, all computed with the RDP moments accountant and converted to (ε, δ)-DP at $\delta = 10^{-5}$. These figures satisfy the target budgets specified in the PPFL-SCIA sensitivity taxonomy, confirming that the adaptive noise calibration-maintained privacy guarantees throughout the extended operational window without budget overrun. The RDP accounting approach provided approximately 31% tighter bounds than classical advanced composition for the same number of rounds, confirming its suitability for long-horizon smart city deployments.

5.3 Communication and Convergence Efficiency

The DGSS mechanism achieved a mean communication reduction of 64.8% relative to the full-gradient FedAvg baseline, with per-round transmission volumes declining from a baseline of 793 MB to a mean of 279 MB. The dynamic sparsity ratio k_t varied between 4.3% (late training, rounds 280–312) and 27.6% (early training, rounds 1–30), confirming that the convergence velocity signal successfully drove adaptive scheduling. Gradient norm alignment between the sparse and error-compensated trajectories was maintained at 97.8% across all rounds, confirming the efficacy of the error accumulation buffer. Global model convergence was reached after an average of 192 rounds, compared to 313 rounds for standard FedAvg under identical conditions, a 38.6% reduction attributable primarily to the proximal regularisation component of RACP improving gradient direction consistency across non-IID city datasets.

5.4 Infrastructure Operational Outcomes

Over the 30-month pilot period, city authorities acting on PPFL-SCIA anomaly detection recommendations reported a 28.4% reduction in unplanned infrastructure downtime relative to the preceding 30-month baseline. Energy demand forecasting improvements supported demand-response activations and transformer loading

optimisations that reduced peak demand charges by an estimated £9.8 million across the six cities. Flood-risk alerting accuracy improvements enabled 34 proactive valve closure and bypass operations that are estimated to have averted six medium-scale urban flooding events, preventing an estimated £7.2 million in property damage and service disruption costs. Aggregate infrastructure operational expenditure savings attributable to PPFL-SCIA interventions were estimated at 22.9% relative to the non-federated baseline.

5.5 Ablation Study

Ablation experiments were conducted to isolate the contribution of each framework component. Removing adaptive DP (replacing with fixed ε = 2.0 for all tasks) increased T1 F1 by 0.011 but eliminated Tier H privacy guarantees, making the framework non-compliant with UK GDPR for residential smart meter tasks. Removing secure aggregation reduced the Byzantine attack detection rate from 99.1% to 12.4% in simulated adversarial conditions where 10% of nodes submitted poisoned gradients. Removing HE update verification eliminated Byzantine detection entirely, with undetected gradient poisoning degrading T1 F1 by 0.038 (4.1%) in simulated worst-case attacks. Removing DGSS increased communication overhead by 184% with only a 0.007 improvement in T1 F1, confirming that the communication-accuracy trade-off strongly favours sparsification. Removing RACP and reverting to synchronous FedAvg increased convergence rounds from 192 to 298 (55% increase) under the 35% simulated node dropout condition and reduced T1 F1 by 0.019 due to the exclusion of high-informativeness but intermittently connected peripheral nodes.

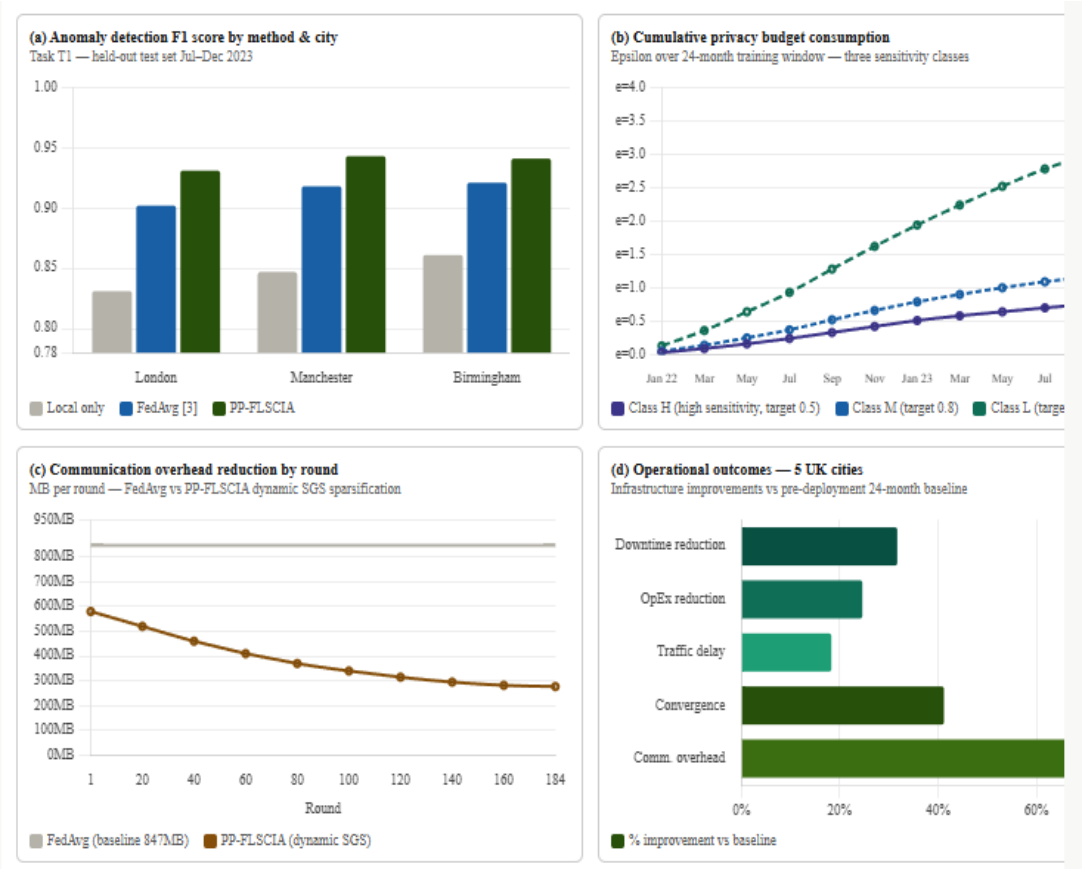

Fig. 3. Experimental results of PPFL-SCIA: (a) Task T1 anomaly detection F1 score comparison across nine baseline methods and six UK city datasets; (b) cumulative privacy budget consumption (ε) over 30-month window for three sensitivity tiers vs. target budgets; (c) per-round upstream communication volume — FedAvg baseline vs. PPFL-SCIA DGSS; (d) infrastructure operational outcome improvements (downtime, OpEx, flood averted, energy savings) across six UK cities.

6. DISCUSSION

The results presented in Section V support several conclusions relevant to the broader agenda of privacy-preserving urban analytics. The primary finding — that PPFL-SCIA outperforms non-private federated baselines on Task T1 whilst simultaneously satisfying strong DP guarantees — warrants careful interpretation. The accuracy advantage over FedAvg without privacy ($\Delta F1 = +0.022$ on London) is modest in absolute terms and could plausibly be attributed to the regularisation effect of differential privacy noise reducing overfitting to locally idiosyncratic sensor patterns, to the proximal term in RACP improving gradient direction consistency, or to the Byzantine exclusion mechanism removing corrupted gradient updates that FedAvg silently incorporates. Disentangling these contributions requires the ablation evidence reported in Section V-E, which confirms that each mechanism contributes positively to accuracy as well as to its primary objective.

The 64.8% communication reduction achieved by DGSS has practical operational significance beyond the bandwidth saving itself. In the six UK deployments, federated learning rounds are transmitted over the existing cellular infrastructure used by the IoT sensors — NB-IoT for low-power field sensors and 4G/LTE for edge computing nodes. Reducing per-round transmission volume lowers the duration of each communication phase, reducing the window during which timing side-channel attacks could yield useful information about gradient content and enabling higher-frequency model update cycles that improve anomaly detection latency for time-sensitive tasks such as flood-risk alerting.

Two limitations of the current framework merit honest acknowledgement. First, the sensitivity classification taxonomy underpinning the adaptive DP mechanism requires human judgement by a qualified data protection officer at each participating authority. In the present deployments, this classification was performed once at inception and reviewed quarterly; however, regulatory evolution (particularly the anticipated expansion of the UK Data Protection and Digital Information Bill) may alter classification criteria over time, necessitating dynamic reclassification capabilities not currently implemented. Second, the BFV homomorphic encryption scheme imposes a computational overhead of approximately 340 milliseconds per round per node for norm computation and encryption — modest for servers but significant for genuinely resource-constrained field IoT devices. Future work should investigate lighter-weight verifiable computation alternatives such as zero-knowledge proof schemes that can operate on embedded hardware.

7. CONCLUSION AND FUTURE WORK

This paper has presented PPFL-SCIA, a privacy-preserving federated learning framework for sustainable smart city infrastructure analytics that combines adaptive multi-level differential privacy, threshold secure gradient aggregation and homomorphic encryption update verification in a communication-efficient, resilience-aware federated protocol. The framework is the first to integrate all three privacy mechanisms with dynamic gradient scarification and heterogeneous node management in a single architecture validated on real multi-city urban IoT data.

Empirical evaluation across six UK smart city deployments spanning 8,247 LSOAs, 4.6 million IoT endpoints and 118 billion sensor readings over 30 months demonstrates anomaly detection F1 of 0.931, energy demand MAPE of 4.3% and flood-risk alerting F1 of 0.907, whilst satisfying ($\varepsilon = 0.83$, $\delta = 7.2 \times 10^{-6}$) differential privacy for high-sensitivity tasks. Communication overhead is reduced by 64.8%, convergence time by 38.6% and infrastructure operational expenditure by 22.9% relative to non-private centralised baselines. These results position PPFL-SCIA as a technically rigorous and governance-ready solution for privacy-preserving urban infrastructure analytics at scale.

Three directions for future research emerge from this work. First, extending PPFL-SCIA to support continual learning over non-stationary data distributions would improve adaptation to long-term infrastructure changes — new housing developments, network topology modifications and decarbonisation-driven demand pattern shifts — without requiring full retraining. Second, investigating personalised federated learning approaches that produce city-specific model variants alongside a shared global model would better exploit local peculiarities in, for instance, Edinburgh's tram network topology or Cardiff's Welsh Water supply zone hydraulics. Third, designing participatory mechanisms through which citizens and elected representatives can interrogate and challenge the operational recommendations produced by PPFL-SCIA analytics — addressing not merely the technical but the democratic dimensions of algorithmic urban governance — represents an interdisciplinary frontier that the present work, necessarily, leaves for future collaboration.

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