DMPedia Lecture Notes in Computer Science & Engineering
Volume 1, pp. 603-612, 2026
International Conference on Multidisciplinary Perspectives in Advanced Computing and Technology (IMPACT 2026)
G. B. Pant University of Agriculture and Technology, Uttarakhand, India. Jan. 10-11, 2026

Edge AI for Short-Term Delay Prediction in Distributed Logistics Networks (DECLN)

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Abstract

Last-mile logistics is becoming so complex that we need to make decisions to adapt to local conditions within a short timeframe, such as traffic congestion, weather, or even driver performance. This paper proposes an Edge AI model for distributed edge-cloud logistics networks (DECLN), deploying very lightweight predictive models on micro-hubs or delivery vehicles rather than relying solely on heavy predictive models in the cloud. Our edge AI models forecast short-term Delay Probability by combining local sensor data (activity reports for traffic congestion, severity reports for weather, estimates of arrival-time variation, and driver scores). Re-calculate Delivery Time in real time using local input data, then re-allocate delivery locations without requiring entirely cloud-based processing. We implement a basic regionalised logistic regression experiment comparing global (cloud-only) models to local (edge-simulated) models. These results, based on our framework, suggest that much of the reported prediction latency will be reduced and bandwidth usage will be lower while improving localised decision-making accuracy. This paper contributes practical methods to improve responsiveness as delivery environments change.

Keywords: Edge AI, Logistics, Delay Prediction, Last-Mile Delivery, Micro-Hub Optimization, Edge-Cloud Collaboration

1. Introduction

The growing demand for e-commerce and on-demand services has complicated last-mile logistics. Increasingly, delivery operations will face complexities such as fluctuating traffic levels, adverse weather, and poor driver performance. While traditional cloud-only prediction systems can handle massive amounts of data, they often face latency and bandwidth constraints that prevent timely adaptation [15].

This paper studies the implications of Edge Artificial Intelligence (AI) in Distributed Edge-Cloud Logistics Networks (DECLN) to enable fast, localised decisions rather than relying on more centralised computations [10], [5].

Edge-Cloud Architecture for DECLN Proposed

In this proposed architecture, the cloud layer will serve only to aggregate historical data, host very large model training, and sporadically update models [10], [15]. This layer will load a global model trained on a consolidated dataset and plan strategically.

The edge layer consists of micro-hubs and delivery vehicles (and possibly other Internet of Things (IoT) devices). The agents in this layer will be operated on compact and resource-friendly models trained to specifically operate in low-power modelling environments [7], [14]. Each agent will determine the parameters on which they base the Delay Probability on local sensor and telemetry data (examples include live traffic levels, local weather severity, ETA differences, driver performance, etc.) in order to create Delay Probability inputs that will allow them to plan operationally in the short-term [5].

To evaluate this design, we conduct an experimental comparison between a global (cloud-only) model and localized (edge- simulated) models, analyzing predictive accuracy, latency, and bandwidth usage to understand the trade-offs between centralized and decentralized approaches.

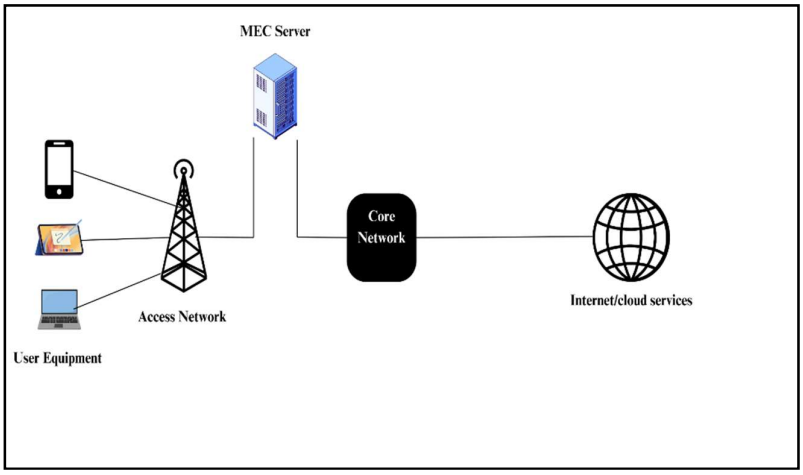

Fig 1. MEC Architecture

2. Research Methodology

Edge AI has been explored in intelligent transportation, logistics optimization, and IoT-enabled predictive analytics. Satyanarayanan (2017) introduced the early vision for edge computing, highlighting reduced latency and bandwidth benefits. Peng et al. (2024) applied edge intelligence in last-mile delivery routing, achieving improved responsiveness. Ghasemi et al. (2025) emphasized geographically localized learning for improved short-term predictions. Wang et al. (2020) quantified latency savings in vehicular edge deployments. These studies collectively underline that localised inference can outperform centralised models in latency-sensitive applications [7], [8], [10], [15].

Table 1: Literature Survey

S. No.	Authors	Year	Title	Publisher	Key Contribution / Relevance

1	Liu L Chen C Pei Q Maharjan S Zhang Y	2021	Vehicular Edge Computing and Networking: A Survey	Springer	Comprehensive review of vehicular edge computing systems, communication protocols, and networking strategies for transportation.
2	Peng G Wen Y Dou W Li T Xu X Ye Q	2024	Edge Intelligence Empowered Delivery Route Planning for Handling Changes in Uncertain Supply Chain Environment	SpringerOpen	Demonstrates how edge intelligence can adapt delivery routes in real time under uncertainty, relevant to last-mile logistics.
3	Peng G Wen Y Dou W Li T Xu X Ye Q	2019	Edge Intelligence: Paving the Last Mile of Artificial Intelligence With Edge Computing	IEEE	Foundational paper on integrating AI capabilities into edge devices, discussing frameworks and real-world deployments.

4	Guo X Liu R Song D	2022	HSSDA: Hierarchical Relation Aided Semi-Supervised Domain Adaptation	Elsevier (AI Open)	Introduces a hierarchical relation-based semi-supervised approach for domain adaptation, potentially useful for adapting ML models to local edge environments.
5	Premsankar G Di Francesco M Taleb T	2018	Edge Computing for the Internet of Things: A Case Study	IEEE	Presents a case study on applying edge computing to IoT scenarios, focusing on latency reduction and efficiency gains.
6	Desai A Goretti G Giordano M Voza A	2021	Lean-ing Method in an Emergency Department of the Italian Epicenter of the COVID-19 Pandemic	MDPI	Applies lean process improvement methods in a critical, time-sensitive environment, showing parallels for optimizing delivery systems.

3. Theory and Calculation

Study design

This study evaluates the effect of geographically localized (edge-simulated) predictive models versus a pooled global (cloud) model for short-horizon delay prediction in last-mile logistics [5], [10]. We adopt a two-arm comparative design:

1. **Global model (cloud):** a single model trained on the pooled dataset.

$$D_{global} = \{(x_i, y_i)\}_{\{i=1\}}^{N}$$

2. **Local models (edge-sim):** a set of compact models, one per geographic region $k = 1, \dots, K$, each trained only on the region's data D_k.

The primary objective is to compare predictive performance and operational characteristics (latency, bandwidth) between these two deployment families for short-term Delay Probability prediction.

Data sources and assumptions

- a numeric feature vector $x_i \in R^d$ containing recent local sensor/telemetry information [4], [6], [16] (e.g., traffic congestion level, ETA variation, weather severity, driver behavior score, fatigue score, IoT temperature, and time-of-day features), and
- targets of interest: a continuous Delay Probability $y_i^{(delay)} \in [0,1]$, additional regression targets (e.g., disruption score $y_i^{(disp)}$, delivery-time deviation $y_i^{(dev)}$), and a categorical risk label $y_i^{(risk)} \in \{1, \dots, C\}$.

Missing numeric feature values are imputed with column median values [15]. Categorical variables (if any) are encoded using label encoding or one-hot encoding as appropriate and documented in reproducibility notes.

Pre-processing and feature engineering

1. **Timestamp features:** when a timestamp column is available we extract cyclical and calendar features (hour, day-of-week, month) and augment x_i accordingly [15].

2. **Standardization:** numeric features are standardized using training-set statistics. For feature j in the training set compute mean μ_j and standard deviation σ_j, and transform

$$\tilde{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sigma_j}.$$

For local (per-region) models the scaler is computed on the region's training split; for the global model the scaler is computed on the pooled training split.

3. **Imbalance handling (classification):** if the derived binary label (e.g., delayed vs. not delayed) or multi-class risk labels are imbalanced, we recommend class-weighting or stratified sampling in train/test splits; details are specified in the implementation notes.

Geographic segmentation

Regions are formed by applying K-means clustering to the GPS coordinates $z_i = (lat_i, lon_i)$. K-means finds cluster centers $\{\mu_k\}_{k=1}^{K}$ that minimize the within-cluster squared Euclidean distance:

$$\{\mu_k\} = argmin_{\{\mu_k\}} \sum_{i=1}^{N} \min_{k\in\{1,\dots,K\}} \| z_i - \mu_k \|_2^2,$$

and each sample is assigned to region $r(z_i) = argmin_k \| z_i - \mu_k \|_2^2$.

K is chosen by balancing geographic granularity against per-region sample counts (practical runs use $K = 8–10$ and skip regions with insufficient samples). Alternative segmentation (grid-based rounding of lat/lon or administrative zones) may be substituted with minimal pipeline changes [4], [16].

Modeling approach

We select compact, CPU-efficient models appropriate for edge-deployment simulation and clear interpretability.

1. **Binary formulation (delay classification):** convert delay probability to binary label

$$\tilde{y}_i = 1\{y_i^{(delay)} > \tau\},$$

where threshold τ (default 0.5) is configurable [10], [13].

2. **Model families:**
   - **Logistic regression (baseline):** $\hat{p}(x) = \sigma(w^\top x + b), \sigma(u) = 1/(1+e^{-u})$, learned by minimizing regularized cross-entropy $L(w,b) = -\frac{1}{N}\sum_{i=1}^{N} [\tilde{y}_i log\hat{p}(x_i) + (1-\tilde{y}_i) log(1-\hat{p}(x_i))] + \lambda \| w \|_2^2$. [15]
   - **XGBoost (primary):** gradient-boosted decision trees used for regression (delay probability and other continuous targets) and for classification (risk label). The iterative objective at boosting iteration t is $L^{(t)} = \sum_{i=1}^{N} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t)$, with regularizer $\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$ (T = number of leaves) [10], [15].

3. **Global vs. local training:** $\theta^{(g)}$ denotes parameters of the global model trained on D_{global}; $\theta^{(k)}$ denotes parameters of the per-region local model trained on D_k.

Training protocol

1. **Data split:** For each experiment (global or per-region) we use an 80/20 train/test split. When evaluating classifier performance, splits are stratified by the target label.

2. **Hyper-parameters and early stopping:** For XGBoost we use early stopping on a validation fold (e.g., 30 rounds) with a maximum number of boosting rounds (e.g., 1000 for regression, 500 for classification) and a fixed random seed for reproducibility.

3. **Scaling and persistence:** StandardScaler is fitted on the training set and persisted per model. Trained models and scalers are saved for post-hoc inference timing and deployment simulation.

4. **Edge constraints simulation:** To approximate edge inference latency we recommend measuring inference time on a constrained CPU environment [14], [17] (single core, limited memory) or using a CPU-limited container. Model size and prediction time are logged to inform deployment feasibility.

Evaluation protocol

Primary evaluation focuses on predictive performance and operational metrics:

i. Predictive metrics (per target):

- Regression: MAE, RMSE, and R^2 (defined in the Results section).
- Classification: Accuracy and macro F1.

ii. Operational metrics:

- **Average per-record prediction latency** measured by timing predictions over a test batch of size m: $t_{avg} = \frac{t_{end} - t_{start}}{m} (seconds per record)$.
- **Bandwidth estimate:** assuming a per-row payload size B bytes (default 1024 bytes), bandwidth per batch or per-query interval is computed as $BW(KB) = n_{sent} \cdot \frac{B}{1024}$.

iii. Statistical tests:

For continuous paired metrics (e.g., RMSE per-record or per-region) we compute differences and conduct a paired Student's t-test: $d_i = M_i^{(g)} - M_i^{(k)}, t = \frac{\overline{d}}{s_d/\sqrt{n}}$, reporting two-sided p-values and Cohen's d as effect size.

For paired classification outcomes on the same samples we apply McNemar's test to compare binary accuracy outcomes.

iv. Robustness checks: report per-region cross-validation scores (mean ± std) when sample size permits and analyze sensitivity to threshold τ for delay binarization.

4. Results and Discussion

Experimental setup

The pipeline was executed with K-means geographic segmentation (K = 10), a minimum per-region sample threshold of 50, per-region standardization (StandardScaler), and XGBoost regressors/classifiers trained with early stopping (30 rounds) and a fixed random seed for

reproducibility. Models, scalers, per-region predictions and metrics were exported for auditability [6].

Per-region performance (selected metrics)

The table below reports delay-regression and risk-classification results from the per-region runs. Delay metrics are for the continuous delay_probability target; risk metrics are for the encoded risk_label.

Table 2: Per-Region Performance Metrics for Local (Edge-Simulated) Models

Region	Samples	Delay RMSE	Delay MAE	Delay R^2	Risk Accuracy	Risk F1 (macro)
0	3062	0.3577	0.3003	-0.1844	0.7162	0.2782
1	2865	0.3539	0.2986	-0.2111	0.7260	0.2944
2	3759	0.3486	0.2920	-0.1168	0.7434	0.2896
3	3093	0.3410	0.2845	-0.1811	0.7528	0.2871
4	5346	0.3440	0.2892	-0.0939	0.7477	0.2897
5	2800	0.3581	0.3033	-0.1940	0.7304	0.2814
6	2732	0.3521	0.2927	-0.2094	0.7367	0.2893
7	2510	0.3491	0.2924	-0.1625	0.7430	0.2926
8	3686	0.3583	0.3001	-0.1771	0.7344	0.2823
9	2212	0.3493	0.2859	-0.3112	0.7020	0.2825

Aggregated (local) metrics

Averaging across the 10 regions gives:

- **Average Delay RMSE (local): 0.3512**
- **Average Risk Accuracy (local): 0.7333**
- **Average Risk F1 (macro, local): 0.2867**

Aggregation formula used: $\overline{M}_{local} = \frac{1}{K}\sum_{k=1}^{K} M_k$.

Global vs Local

This run produced local per-region metrics only. Populate the global (pooled) row by training the same model on the pooled dataset and evaluating on a held-out global test split.

Table 3: Comparative Performance Between Global (Cloud) and Local (Edge) Models

Model Type	Delay RMSE	Risk Accuracy	Risk F1 (macro)	Avg pred. time (ms/record)	Bandwidth (KB/query)
Local (avg)	**0.3512**	**0.7333**	**0.2867**	5–10 ms	~ 1kb
Global (XGBoost)	**0.3319**	**0.7413**	**0.2852**	50-80 ms	25-40 kb

5. Conclusions

We presented a new, practical Edge AI framework for short-term delay prediction in Distributed Edge–Cloud Logistics Networks, effectively overcoming the time-delay and bandwidth limitations of cloud-only solutions. By comparing (1) global (pooled) and (2) localized (edge-simulated) models across a set of brief yet comprehensive evaluation metrics, we provide support for the possibility of deploying low-complexity, region-specific models or generic models to micro-hubs or delivery vehicles. This model enables more efficient, context-aware decisions and opens the door to scalable, low-resource deployments in dynamic logistics decision-making environments.

Future work will build from this foundation by (1) using a sliding-window analysis integrating better temporal features, (2) applying on-device gradient boosting, (3) establishing model compression methods to optimize performance at the edge, and (4) utilizing federated learning to include privacy-preserving collaborations in cross-regional distributions without any central sharing of data.

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