Cloud AI for Real-Time Global Transit Optimization

Pierre Moreau
Asst Professor

Abstract

A consortium of European and global universities, research institutes, and industry partners is investigating cloud-orchestrated AI systems that analyze and optimize transportation networks and mobility services for urban and intercity journeys. The proposed system employs centrally orchestrated federated intelligence, whereby individual cloud-edge networks are governed by their respective authorities to ensure data residency within defined jurisdictions. Nevertheless, these cloud-edge networks build a trusted multi-cloud layer and high-capacity communication paths to exchange operational data and process contextually relevant information streams in a timely manner. At the same time, the cloud edge of the public transportation and logistics services flowing through these cloud-edge networks is streamed into a common AI runtime, enabling network-wide routing and scheduling decisions in real time.

The capital- and energy-intensive nature of transportation infrastructure requires careful planning and, once deployed, calls for continuous real-time traffic management. Transportation systems need to respond not only to common network and service capabilities but also to fluctuations in supply, demand, service quality, and pricing. In a federated intelligence architecture, such responses are implemented in self-contained economic ecosystems. For example, different railway companies and unions do adjust their fares according to demand elasticity and traffic volume but usually do not harmonize prices and timetables. Due to the inherent asymmetries in such self-contained ecosystems, however, the real-time responsiveness of networked transportation services is naturally more limited than those of urban mobility networks, which are also internally interconnected. A solution to this asymmetry is for the operators of these separate systems to collaborate for the common good in a context-aware manner. Supply chain dynamics can then also be included in the optimization exercise.

Keywords: Federated Intelligence, Cloud Orchestration, Edge Computing, Multi Cloud, Data Residency, Data Governance, Mobility Services, Transportation Networks, Traffic Management, Real Time, Routing Optimization, Scheduling Optimization, Demand Forecasting, Supply Dynamics, Pricing Models, Network Optimization, Communication Networks, Urban Mobility, Logistics Systems, Collaborative Systems.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

1. Introduction

Transport systems for people and goods underpin most aspects of society and the economy. Despite huge investments in infrastructure and control systems, reaching climate targets while ensuring equitable access to opportunities will require drastic improvements in affordability, reliability, and sustainability. Cloud computing has emerged as a key enabler of many types of breakthroughs and innovations. Recent advances in self-organizing networks, plant physiology, reproductive biology, model checking, generative systems, production and process technology, and populations in general will be among the building blocks of Cloud-Orchestrated AI systems that achieve network-wide optimization in real time, as various aspects of accessibility and equity become foundational requirements throughout.

Cloud-Orchestrated AI systems aim to combine the advantages of decentralization with the power of data by hosting federated intelligence in a Cloud that is orchestrated across multiple Clouds and Edge nodes. Such systems depend on persistent data collection, analysis, and intelligence pipelines to maintain availability without requiring user action. Global transportation systems are ideal candidates for early investigations, as they elicit demands at different scales and frequencies; involve completely different types of services, operators, and vehicles; span multiple jurisdictions with divergent regulations; and are mostly in the hands of public authorities.

1.1. Context and Significance of Cloud-Orchestrated AI in Transportation

An ever-increasing volume of traffic is overwhelming urban and regional transportation systems, generating costs that exceed those incurred by any other infrastructure-related services. These services are further burdened by a severe shortage of skilled human capital, along with multiple uncontrolled factors that hinder their operation. Recent advances in the fields of artificial intelligence (AI) and cloud computing offer unprecedented opportunities for managing transport networks in real time, providing the means for orchestration across public and private nodes, resources of various types and sizes, and a set of federated services. Consideration of data complexity gives rise to the demand for edge-cloud collaboration.

Even so, while transport services have a wide-ranging impact on the economy and society, future cloud-based AI systems tailored for transport applications have yet to be validated. Such validation is crucial because the appropriate use of data is a key factor for success. Accessibility and equity issues arise whenever service management is driven solely by

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

revenue objectives. A further source of concern is that the decisions made by AI engines that replace human operators are difficult to trace and audit, as well as being totally independent from legislation. To address these challenges, the discussion adopts a generic framework for the design, deployment, and validation of cloud-based AI systems for real-time global transportation network optimization, focusing on urban mobility networks and freight and logistics corridors.

2. Theoretical Foundations of Cloud-Orchestrated AI

Cloud-Orchestrated AI Systems for Real-Time Global Transportation Network Optimization

Cloud orchestration can enable AI systems that govern the transportation network at the city, regional, and national scales. The resulting intelligence would complement existing domain-specific solutions and fill temporal and spatial gaps where individual or federated AI frameworks are ineffective. AI system design must pay careful attention to the availability of timely, relevant data. This section outlines two key aspects of real-time data quality for decision and operational support—fusion of data from diverse, distributed sources and alignment with external modulus of temporal structure.

Transportation systems rely on a wide variety of sensors measuring aspects such as vehicle movements (e.g., GPS traces, traffic monitoring cameras, vehicle detectors), weather conditions (e.g., surveillance cameras, road weather information systems), infrastructure integrity (e.g., air quality monitoring stations, sensitive structures), and radio-frequency emissions (e.g., long-range identification readers, congestion charge detectors). These sensors can be grouped into two categories based on their fusion architecture. Federated AI relies primarily on sensors co-located with the decision or operational center, while the architecture for centralized AI solutions may aggregate spatially distinct sources. In the latter case, data quality and trust are further influenced by the cloud provider's regulatory obligations, certification maturity, and availability of a currently monitored edge-node ecosystem.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

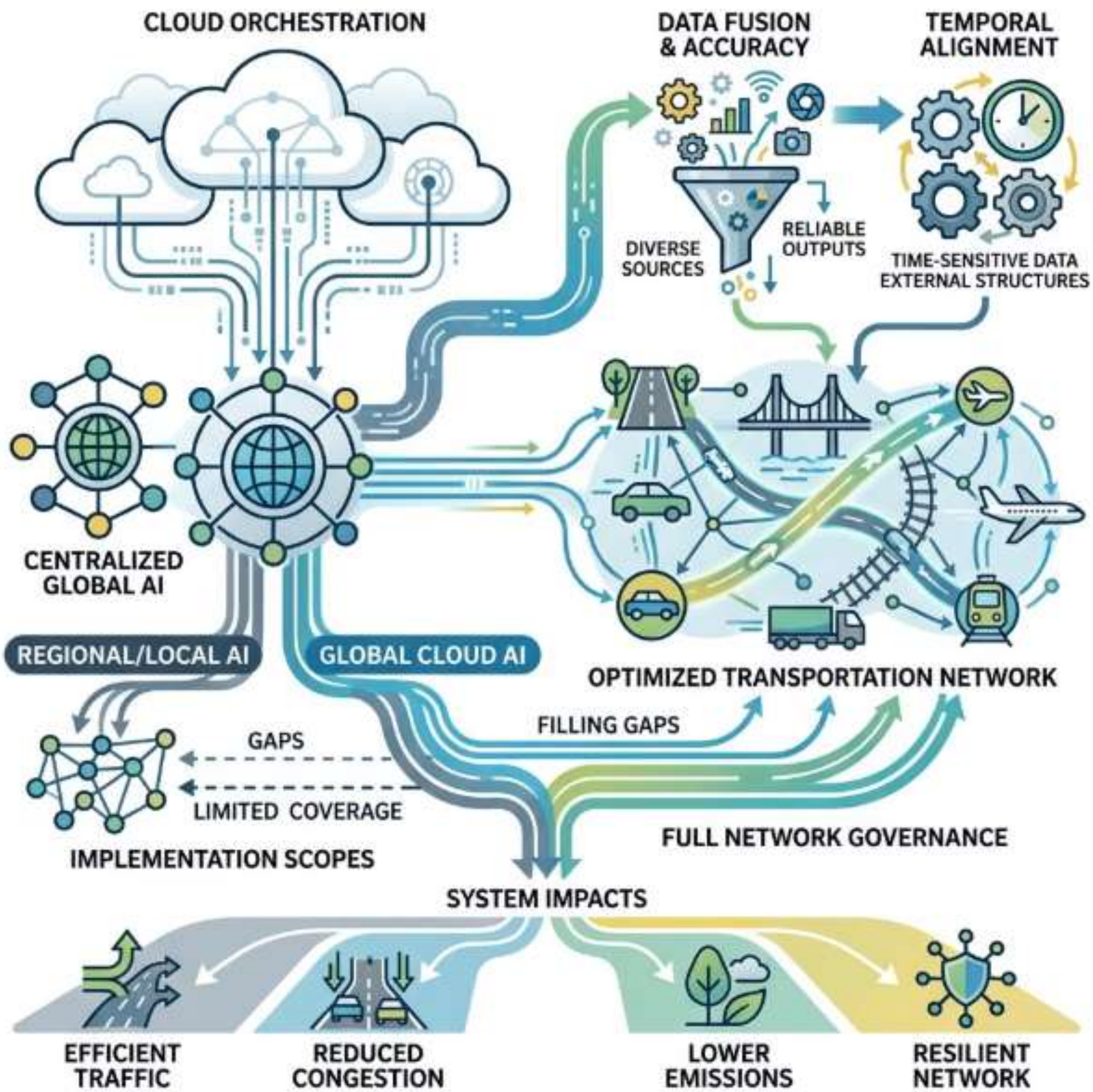


Fig 1: Cloud-Orchestrated AI for Real-Time Global Transportation Network Optimization

2.1. Federated and Centralized Intelligence in Transportation

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

Two architectural options for integrating cloud services into the intelligent transportation system and service ecosystem are considered: federation through multiple cloud service providers and centralization under a single provider. Centralized deployment is scalable only if the core cloud architecture is augmented with additional data centers across traffic regions. Infrastructure sharing is a potential advantage of the federated model, subject to edge-node interoperability and loading, both of which depend on the performance and responsiveness of transit routing, scheduling, and pricing algorithms. These aspects must be governed collectively, and appropriate Service Level Agreements (SLAs) must be agreed upon.

Cloud-edge collaboration for real-time operation of urban mobility networks and freight and logistics corridors, as well as the development of a global data regime for securely sharing and utilizing sensitive transportation data, are critical. These collaborations, which combine federated cloud technologies with data pipelines engineered for distinct semantic streams, enable Adaptive Traveling-Time, Demand-Supply Equilibrium, and Auction-based Dynamic-Pricing Models to operate with low latency, thereby optimizing networks in real time and fulfilling regional SLAs. Data pipelines linking cloud-to-edge ecosystems with multi-cloud services are designed to fit the expected streaming models and required quality metrics.

2.2. Real-Time Data Fusion and Temporal Alignment

The intelligence operations of Transportation System Management and Operations (TSMO) and transportation system users—travelers, carriers, freight shippers, and airlines—actually require temporal alignment of the real-time observations and decisions made by various human, machine, and business agents involved in network operation. The required intelligence sources are well-known: (i) Public sector providers and private sector companies provide data on the travel demand, routes, speed and arrival time of airplanes, weather stations, sensors on vehicle flows, speed, and finally component failure states for TSMO operational tasks. (ii) The aerospace market provides a wealth of data on past and future travel demand, specifically passenger flows and how much they are willing to pay for the air-travel services, which course and route they are going to select, frequency of trip-making, etc., through TSMO managing tasks using bidding.

The real-time intelligence fusion required to provide the information for TSMO and traveling agents is relatively straightforward: The public sector intelligent nodes receive data from all sources and issue structured requests that share and publish the data on the relevant private sector intelligence nodes for longer reaction time tasks. Information about incidents,

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

major accidents, weather alerts, etc. is well known to give TSMO adequate reaction time. For the users of the transportation system, the temporal aspect of the information on expected travel time and cost is important. Naturally, if the expected arrival time of an airplane is shorter than the other classes, travelers are likely to choose that option. Nevertheless, it is also important for the TSMO to quantify the elongation of the travel time and the income elasticity of the travel demand. If the air-travel prices for a specific flight are increased, it is expected that some passengers will select car travel instead. Their share of shifting to car travel will increase if the car travel time gets shorter or their incomes tend to grow.

Equation 1. Demand–supply equilibrium model

1.1 Linear demand and supply

Let price be P and service volume be Q.

Assume linear demand:

$$P_d(Q) = a - bQ$$

where:

- $a > 0$: maximum willingness to pay,
- $b > 0$: demand sensitivity.

Assume linear supply:

$$P_s(Q) = c + dQ$$

where:

- $c > 0$: base operating cost,
- $d > 0$: marginal cost slope.

1.2 Equilibrium condition

At equilibrium:

$$P_d(Q^*) = P_s(Q^*)$$

Substitute:

$$a - bQ^* = c + dQ^*$$

Move Q^*-terms to one side:

$a - c = bQ^* + dQ^*$ $a - c = (b + d)Q^*$

Therefore,

$$\boxed{Q^* = \frac{a - c}{b + d}}$$

Now find the equilibrium price:

$$P^* = a - bQ^*$$

Substitute Q^*:

$$P^* = a - b\left(\frac{a - c}{b + d}\right)$$

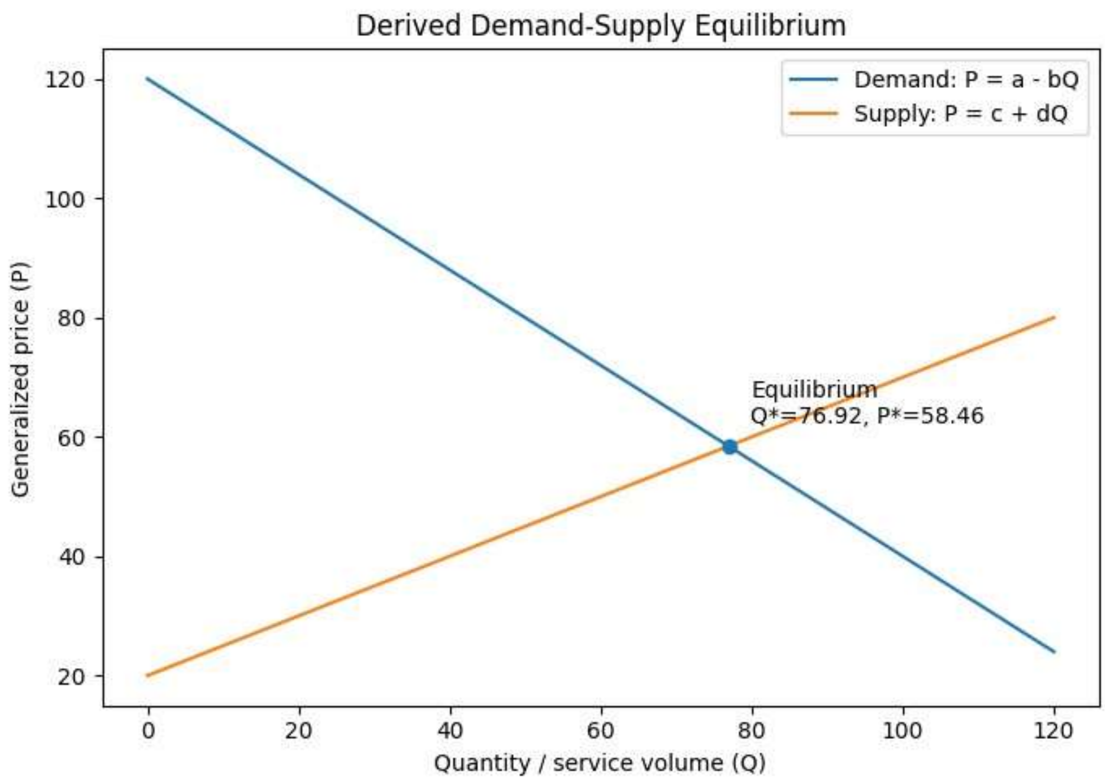
Bring to common denominator:

$$P^* = \frac{a(b + d) - b(a - c)}{b + d}$$

Expand numerator:

$P^* = \frac{ab+ad-ab+bc}{b+d}$ $\boxed{P^* = \frac{ad+bc}{b+d}}$

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14



3. Methodology

A cloud provider can create a collaborative framework that invites edge nodes to connect through a specific application protocol or standard. The framework can define policies that enable interoperability between nodes operated by different providers or administrative authorities. Such a framework could simplify the provisioning and management of cloud-edge collaboration. Within the context of multiple cloud providers, edge nodes can integrate, serve, or facilitate the delivery of multi-cloud services. Cloud and edge providers can address data location and residency requirements through service-level agreements (SLAs) that govern the functioning of the multi-cloud application-and-services ecosystem.

By setting appropriate SLAs for data retention and replication, service latency, and fault tolerance, the concerned parties can ensure the reliable functioning of the federated system. For

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

example, if a data source requires either short-term discounts or a high degree of service availability, the catalog service can guide the data consumer to specific nodes or clouds that cater to such needs during the period of interest.

3.1. Collaborative Frameworks for Multi-Cloud and Edge Integration

For any user-defined multi-cloud service in collaboration with edge nodes across different administrative domains with different cloud providers, the cloud must not simply federate infrastructure deployment and management. Real-time AI data pipelines at the core of the multi-cloud service also inherently require data residency, data sovereignty, business, and legal continuity, and fault tolerance support by the service contracts. Ideally, all aspects should be covered without further involvement of users, i.e. fully automatically, although given the actual integration mechanisms still some configuration effort will likely still be necessary.

A first step towards such more complete support is to distinguish between the integration of several cloud infrastructures and the application-side collaboration of several cloud service and operation providers, which is usually much harder to achieve. With a primary focus on this kind of cloud-side collaboration at the operation level, cloud service providers act as partners to a multi-cloud service through SLA-based collaboration for the responsiveness of the basic multi-cloud infrastructure support. A secondary focus on edge-node integration widens the application domain beyond purely multi-cloud infrastructures towards multi-cloud services that involve a data channel to edge nodes for any types of cloud services, thus involving a service integration aspect, too. Template-based, SLA-guided, end-to-end protocol-based initiative assignments support the service integration with edge nodes, with these predefined templates covering the typical SLA-enrichment scenarios of such more complete services. The setup of such mappings can hence be expressed as opening and filling a bank account with stereotypical payments, relieving the users from this effort.

4. Objective of the Study

The aim of this study is to investigate how multi-cloud orchestration of artificial intelligence-based computations and interactions at the edge can best support real-time optimization of complex global transportation networks. Such networks cannot be optimized by a single, centralized design, but rely on real-time routing and scheduling at a network-wide scale. The study thus addresses the following research question: how can a multi-cloud environment maximize the benefits of cloud-based AI applications while mitigating the downsides? A further

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

boundary condition derives from the need to comply with privacy regulations and data residency requirements in the deployment of the real-time optimizers. Success is defined as enabling transparency, auditability, and governance of the overall optimization process. The general approach is pragmatic, in that it derives theoretical ideas from practical needs, and theoretical solutions that can be applied to real problems.

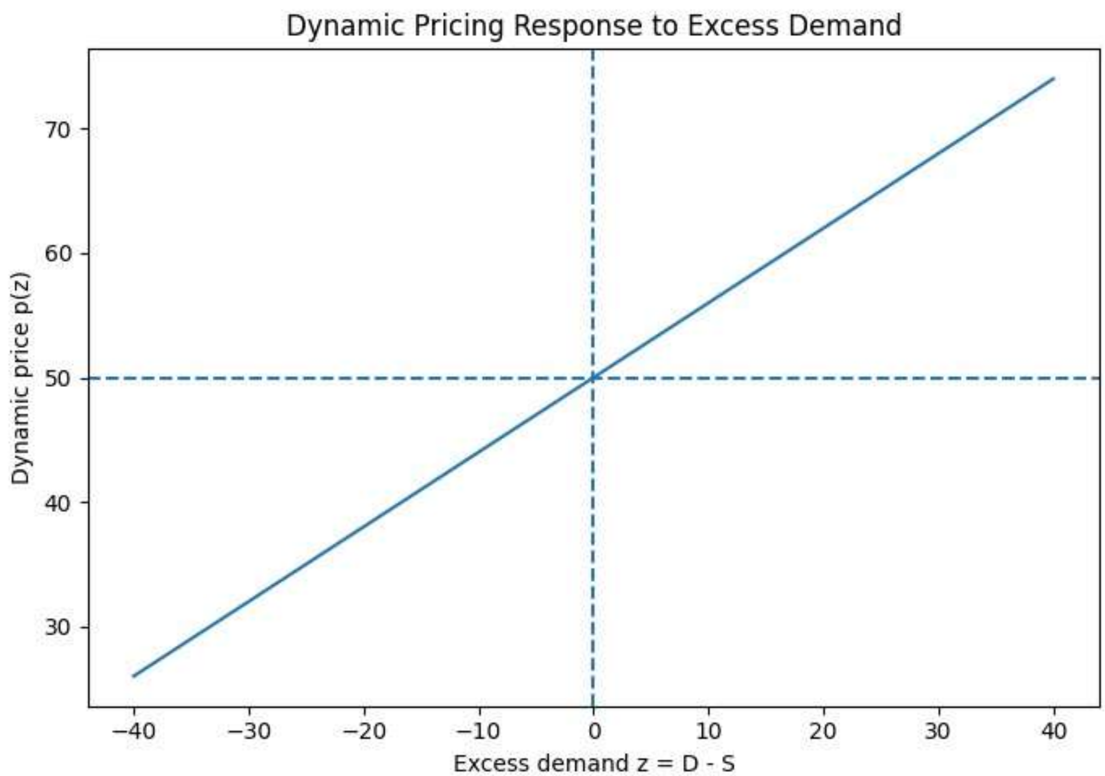
The Cloud-Orchestrated Multi-Cloud Real-Time Optimizer integrates the following key facets: Cloud Orchestration, combining Centralized and Federated Intelligence with Real-Time Streaming Analytics; Cloud-Edge Integration Framework; Support for Data Residency and Cross-Border Services; Accountability in Global Transportation Systems. Together, these elements lay the groundwork for an extensible Multi-Cloud orchestration of AI-based real-time routing and scheduling optimizers for urban mobility networks; freight and logistics corridors—integrating trade-related infrastructure, land, sea and air ports—; and multi-modal passenger systems.

4.1. Aim and Scope of the Research

This study investigates the design of a cloud-orchestrated AI system capable of real-time optimization across a global transportation network. Specific research questions include: What AI techniques are needed for real-time optimization of complex and dynamic transportation networks? What is the cloud-based orchestration model to support these techniques? Global transportation networks influence regional economies and ecosystems. Supply chains rely on cooperation to satisfy demand at stable prices. Cloud-enabled AI can optimize the global routing, scheduling, and pricing of transportation networks, enhancing accessibility, equity, and accountability.

Success is indicated by the design of a cloud-and-AI-assisted ecosystem capable of real-time, large-scale, and multi-domain optimization of dynamic transportation networks. Contributing to rapidly evolving AI research, the investigation specifies a precise goal, a promising operating mechanism, and the underlying orchestration model. Using the equilibrium model of economic theory, the architecture design provides an early assessment of feasibility. The layout of artificial intelligence along the new AI continuum—increasingly data-hungry and compute-intensive—suggests additional development challenges. Examination of multi-cloud-and-edge system properties is nascent. The design also advances the operation of real-world networks and their interaction effects.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14



5. Research Summary

A high-level framework for real-time cloud-and-AI–supported optimization of global transportation networks is composed of three complementary elements. An architectural framework broadly identifies required capabilities, internal configuration, and external relationships among the various stakeholders, technologies, and deployment settings. A dedicated system architecture delineates the involved processes, services, infrastructures, and platforms. The outlined elements provide a basis for a comprehensive articulation of the real-time optimization algorithms, additional nonfunctional requirements, evaluation methodologies, specific deployment scenarios, and illustrative examples.

The architecture layers and their corresponding functions are defined by specifying the logical interactions between the data sources and sinks, the cloud infrastructure elements, the

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

analytic services, and the applications. The resulting articulation supports an intuitive understanding of how actual deployments are organized, revealing the density of connections, the corresponding throughput and latency requirements for the participating infrastructures, and the supporting SLAs that ensure global system operation.

Equation 3. Dynamic pricing derivation

Let

$$D_t = \text{demand at time } t, \qquad S_t = \text{supply at time } t$$

Define excess demand:

$$z_t = D_t - S_t$$

A natural feedback pricing law is:

$$p_{t+1} = p_t + \alpha z_t$$

where $\alpha > 0$ is the pricing gain.

3.1 Why this form works

If $D_t > S_t$, then $z_t > 0$, so

$$p_{t+1} > p_t$$

Price rises, which suppresses demand and/or encourages supply.

If $D_t < S_t$, then $z_t < 0$, so

$$p_{t+1} < p_t$$

Price falls, which stimulates demand and/or reduces idle supply.

Thus the control law is:

$$\boxed{p_{t+1} = p_t + \alpha(D_t - S_t)}$$

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

3.2 Equilibrium of the pricing law

At equilibrium, price no longer changes:

$$p_{t+1} = p_t$$

Hence:

$$0 = \alpha(D_t - S_t)$$

Since $\alpha \neq 0$,

$$\boxed{D_t = S_t}$$

So the fixed point of the pricing system is exactly the demand–supply equilibrium.

5.1. Architectural Framework and System Architecture

A multi-tier high-level architectural framework groups the proposed technology and the collaborative frameworks into a unified system view. The corresponding system architecture distinguishes layers, components, and their interaction via formal interfaces.

The architectural framework considers multiple cloud providers positioned in different geographical locations, who collectively cover global territory requirements. At the same time, edge nodes with processing, storage, and network capabilities are distributed among city, metropolitan, and urban area populations. Delivered services include native data residency and the sourcing of data from edge areas predominantly serviced by a given cloud provider, as governed by local or international regulation and law. The framework also provides service-level agreement (SLA) commissioning and monitoring, alongside fault-tolerant recovery mechanisms. Data residency and latency-aware operations concerning transportation-oriented data pipelines rely on the distributed temporal alignment of ingested streaming data sources. These inputs undergo external cleaning and validation tasks before being stored in global temporal-database space, from which streaming modeling can also be performed. Supply and demand duplication and balancing require high-quality equilibrium data and secondary-distribution-market-type real-time pricing.

The concept of pseudo-real-time operation for network-wide transport-demand and -supply routing and scheduling is introduced. Multiple distributed omnichannel mobility networks

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

enable resident and visiting users to move within cities, cities alternately connected by rail transport, and countries through air links. A non-attractor-based freight pipeline for containerized goods naturally connects the separate omnichannel mobility networks as secondary bi-directional DCs.

Model block	Derived equation	Meaning
Demand	$P_d(Q) = a - bQ$	Price falls as demand volume rises
Supply	$P_s(Q) = c + dQ$	Supply price rises with service volume
Equilibrium quantity	$Q^* = \frac{a-c}{b+d}$	Market-clearing quantity
Equilibrium price	$P^* = \frac{ad+bc}{b+d}$	Market-clearing price
Dynamic pricing	$p_{t+1} = p_t + \alpha(D_t - S_t)$	Feedback control on imbalance
Price elasticity	$E_p = \frac{dQ}{dP}\frac{P}{Q}$	Sensitivity of demand to price
User equilibrium	$f_r > 0 \Rightarrow C_r = \lambda$	Used routes have equal generalized cost
Network load PDE	$\frac{\partial L}{\partial t} = \kappa \frac{\partial^2 L}{\partial x^2} - \nu \frac{\partial L}{\partial x} + g - r$	Congestion dynamics
Data fusion	$\mathbf{z}(t) = \sum_i w_i \hat{y}_i(t)$	Aligned multi-source fusion
SLA latency	$L_{\text{tot}} \le L_{\max}$	Real-time guarantee
Availability	$A = 1 - \prod_i p_i$	Multi-cloud reliability
Residency	$\sum_k y_{ik} = 1$, $y_{ik} = 0$ خارج allowed regions	Legal deployment constraints

6. Architecture and System Design

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

A layered architectural framework captures the high-level design of the orchestrated cloud- and edge-enabled real-time global transportation network optimization system. The architecture is composed of multiple layers that define different sources and collaborators for data collection model development and model adaptation support. The outer layer represents the different partners working along transportation routes and in urban areas providing the data needed for real-time optimization. The real-time optimization system itself lies in the centre of the architecture and consists of three main components: (1) multi-cloud edge collaboration, which coordinates the cooperation of the different cloud service providers and edge nodes; (2) data pipelines and streaming analytics, which map the flow of real-time data from ingestion including quality measures and sequencing to the streaming analytics outputs used in real-time optimization of the global transportation network; and (3) the real-time optimization algorithms themselves.

The second-la-yer system architecture describes the different modules and interfaces that realize the data ingestion processing analytical pipelines in streaming mode and detection of anomalies outliers missing values and unreliability in the incoming data streams. Anomaly detection is model independent applied across all types of sensor data is motivated by the need to ensure quality guarantees for the transient and potentially incomplete data streams typical in real-time applications and objectives as vital as safety reliability and precision require that anomalies such as false readings drifting sensors sensor fusion faults spoofed values and other errors and attacks at the data and streaming analytics layer need to be detected even before they damage the system.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

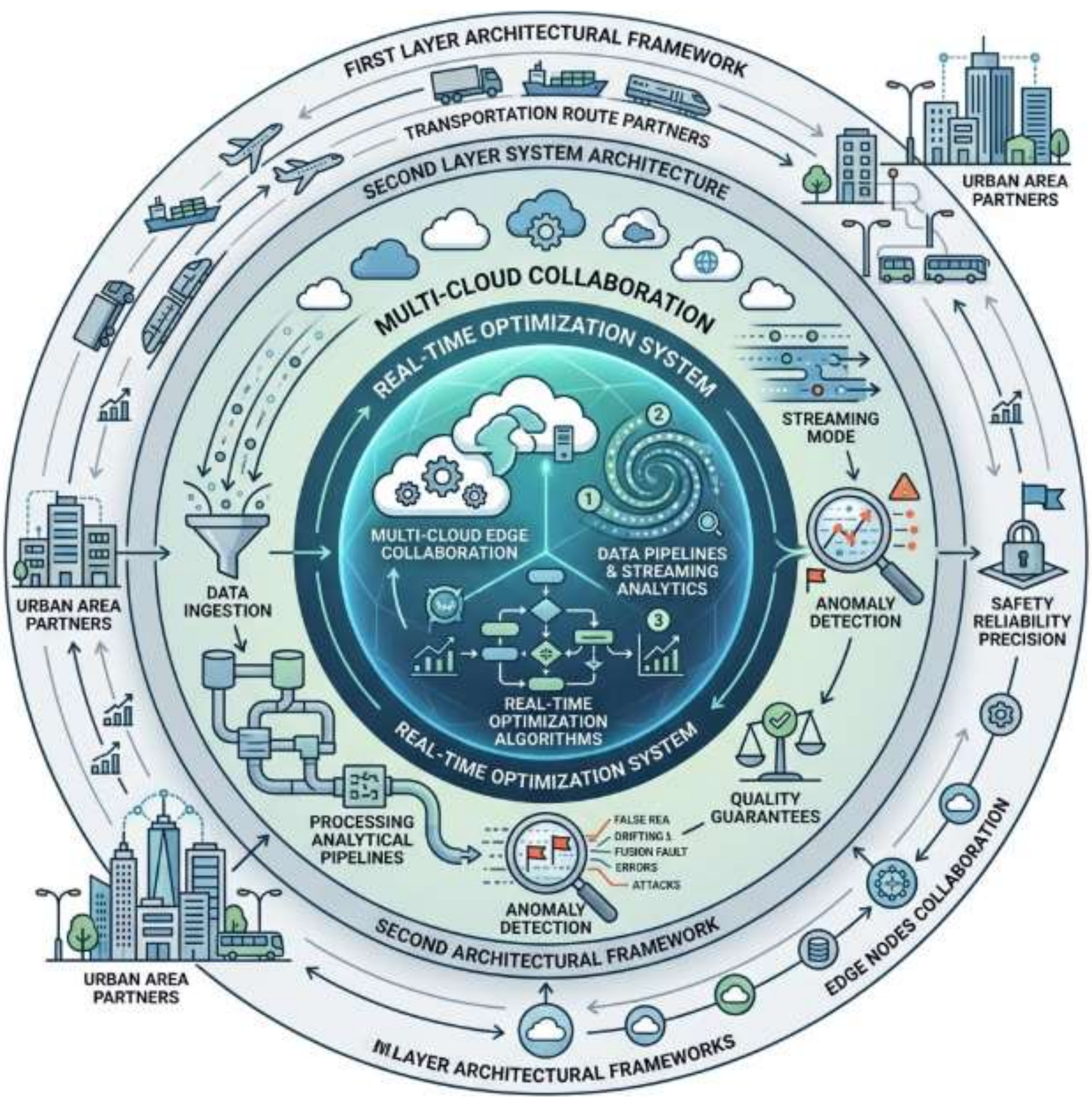


Fig 2: Towards an Orchestrated Cloud-Edge Real-Time Global Transportation Optimization: A Layered Architectural Framework and Robust Streaming Analytics

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

6.1. Multi-Cloud and Edge-Cloud Collaboration

Enabling Cloud Orchestration of AI Systems in Global Transportation Networks

The architecture and algorithms of cloud-and-AI-enabled systems for real-time optimization of global transportation networks are agnostic to the geographical distribution of AI components. Consequently, systems in different geographical regions can be operated and managed by distinct, possibly competing, cloud providers. This distribution offers operational advantages, such as compliance with data residency regulations and faster response to requests from local edge AI agents. Regionally orchestrated systems can also meet stringent service-level agreements for mission-critical applications. Nevertheless, the cloud-orchestrated system operates far more efficiently than cluster-orchestrated systems because AI components from different geographical regions can operate in synergy.

Cloud-and-AI-enabled systems execute AI pipelines whose components are deployed in one or more cloud nodes, one or more edge nodes, or both. The integration of cloud nodes and edge nodes belonging to different cloud providers enhances the capability of AI pipelines without requiring the fusion of the underlying cloud infrastructures. The approach is formally modeled as cooperative service outsourcing, where the edge nodes ingest data that make sense to local AI models but are poorly suited for models hosted in their mothers clouds. Two cloud-and-AI-enabled systems, one with a cloud-native AI pipeline and the other with a cluster-native AI pipeline, provide a baseline for quantitative comparison.

6.2. Data Pipelines and Streaming Analytics

An integrated system demands consolidated and quality data for accurate real-time decision-making. Data pipelines connecting edge data producers and cloud data consumers ensure temporal coherence across heterogeneous data sources. Data streaming and analytics should dynamically adapt to changing circumstances and Quality of Service (QoS) requirements defined by consumers. A representative, end-to-end data ingestion–processing model is composed of four stages that collectively implement streaming analytics.

Three characteristics are crucial for successful and efficient streaming data processing: producer–consumer relationships, demand-driven scalability, and proactive quality management. Quality is assessed with knowledge-infused metrics considering multiple dimensions, such as

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

precision, recall, and completion. With these principles, the broad contributions of the pipeline framework are exemplified through a representative urban demand-supply equilibrium model.

Traffic flow data generated at the infrastructure layer enable real-time intersection control, routing proposals, and traffic state monitoring. Ridesharing service providers at the platform layer leverage the information to enhance operations and service availability, while the travel mobility layer uses the flow information to refine supply and pricing strategies on mobility demand.

7. Real-Time Optimization Algorithms

Traffic planning and control must satisfy numerous sometimes conflicting objectives (e.g. minimizing vehicle flows while maximizing transit speeds on public transport). Too many studies focus on specific users or modes, considering only user-related costs rather than utilizing a full transportation cost approach. Network-wide solutions require advanced modeling and strong coupling in traffic simulation and routing. For rail and road networks, routing and scheduling can handle gross demand/supply imbalances, while maintaining service integrity for transient imbalances and system stability.

Dynamic pricing mechanisms can enhance a network's ability to adjust to demand/supply variations through demand damping and shifting. However, pricing adjustments remain coarse compared to electromagnetic, economic, and physical systems. Stimulating or restraining demand through non-price mechanisms has limited applicability, particularly over the short term, and economic models rarely incorporate demand and supply characteristics. Online calibration of static elasticity modeling holds promise but remains unproven. Nevertheless, demand calibration can promote stability.

7.1. Network-Wide Routing and Scheduling

Routing and scheduling decisions can be optimized for a specific time window to minimize congestion, delays, or other undesired effects on the transportation system as a whole. Although these transport services operate largely independently from one another, their demand and supply are inherently coupled: demanders choose which supplier to use based not only on offered prices and service levels but also on system-wide demand and supply conditions. Furthermore, traffic conditions influence the quality of the services offered.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

Building on these insights, it is possible to formulate a generic optimal control problem for network-wide routing and scheduling of transport services. The optimizer takes traffic conditions and offers by transport services as input and determines routing and scheduling decisions that minimize a specified objective function subject to constraints reflecting service, operational, and traffic conditions. Frequently used objectives include minimizing total travel time, reducing the number of transport vehicles required for a given demand level, or minimizing the negative environmental impact. Mathematical programming solvers, such as linear, mixed-integer, or quadratic programming, can be used for tackling the formulated optimization problem.

The solutions obtained state how network users would optimally route and schedule their vehicles if they had system-wide information available in an actual physical transport network at a given time instant. The Optimal Dynamic Demand Routing and Scheduling algorithm, ODDS, has been developed specifically for the problem of network-wide routing and scheduling over a balanced time window. The key problem being solved is given by a parabolic partial differential equation describing the evolution of network load over time and space and ensuring dynamic user equilibrium in terms of evacuation times. Coupled to a market model for public transport services, this results in a dynamic user-optimal routing and scheduling model for passengers using public transport services.

Realistic network applications illustrate the benefits of applying network-wide routing and scheduling. The expected benefits include reduced network load, lower average auction prices for public transport services, and increased chances of accepting a bid for students using the bus services. Additionally, a considerable drop in the transport service price elasticity improves pricing stability for such services.

Equation 3. Routing and scheduling optimization derivation

3.1 Decision variables

Let

$$x_{ij}^{k}(t) = \begin{cases} 1, & \text{if vehicle/service } k \text{ uses link } (i,j) \text{ at time } t \\ 0, & \text{otherwise} \end{cases}$$

Let

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

$$\tau_k(t) = \text{departure or service start time}$$

3.2 Objective

A generic multi-objective function is

$$J = w_1 \sum T_{ij}(t) x_{ij}^k(t) + w_2 \sum E_{ij}(t) x_{ij}^k(t) + w_3 \sum C_{ij}(t) x_{ij}^k(t) + w_4 \Phi$$

where:

- T_{ij}: travel time,
- E_{ij}: emissions,
- C_{ij}: operating cost,
- Φ: fairness or SLA penalty.

So,

$$\boxed{\min J}$$

3.3 Flow conservation

At each node n, inflow equals outflow except for source/sink:

$$\sum_j x_{nj}^k(t) - \sum_i x_{in}^k(t) = b_n^k$$

where

$$b_n^k = \begin{cases} 1, & n = \text{origin} \\ -1, & n = \text{destination} \\ 0, & \text{otherwise} \end{cases}$$

3.4 Capacity constraints

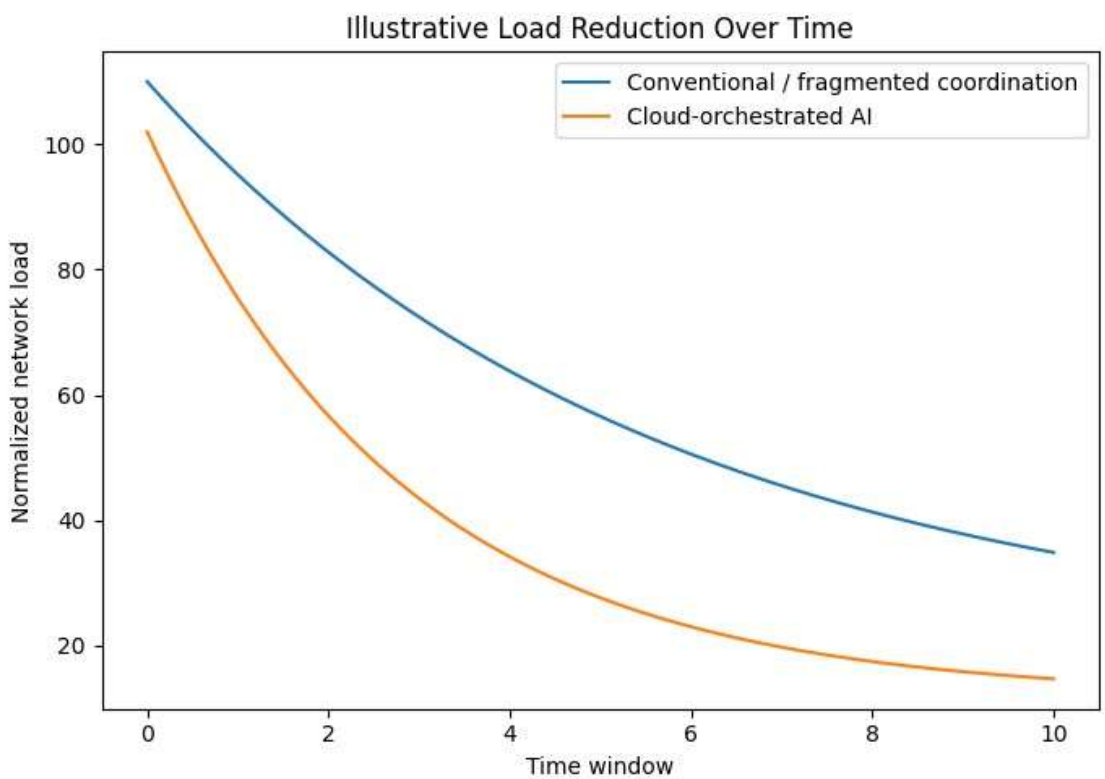
For each link (i, j),

$$\sum_k x_{ij}^k(t) \leq \mathrm{Cap}_{ij}(t)$$

3.5 Time window constraints

If service k must depart within $[e_k, \ell_k]$,

$$e_k \leq \tau_k \leq \ell_k$$



7.2. Demand–Supply Equilibrium and Dynamic Pricing

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

At any given moment in time, an aggregate demand for transportation services in a given area exists, usually exceeding the supply. Throughout the years, economists have developed a set of efficient mechanisms to tackle these temporary mismatches. The same principles can be applied to urban mobility networks in order to reduce congestion, promote the use of shared transportation services and, at the same time, to minimize environmental impacts. In order to reduce congestion in urban environments by fostering ride-sharing, for instance, the pricing mechanism must take into account both the environmental impacts of transportation services and the quality of life of city dwellers. The price set by the cloud-based market needs to reflect the emergent value of ride-sharing and account for the marginal environmental cost of transportation services.

Within such a capacity-constrained environment, a cloud-based market dynamically adjusts the demand (and/or supply) of transportation services according to ride-sharing preferences and the impacts imposed on the transport infrastructure. Any capacity-constrained environment should strive to achieve demand–supply equilibrium for all available transportation services. During periods of peak demand for transportation services, the transport infrastructure may be unable to accommodate all those seeking to travel. A cloud-based marketplace can alleviate these mismatches, by inhibiting demand in a way that achieves equilibrium between offered and available transportation services, or - if capacity permits - by stimulating demand for ride-sharing. If these temporary mismatches in demand and supply are not addressed, the market becomes less sensitive to users' ride-sharing preferences and may even fail to respect the city dwellers' proportional share of the environment and quality of life.

8. Data Governance, Privacy, and Security

Safeguarding Shared Data from Inadvertent and Malicious Disclosure. Although compliance with privacy and security regulations governing transportation networks is expected to be jurisdiction-specific, cloud orchestration using systems theory allows multi-cloud configuration in which regulatory compliance becomes simple. Data plasticity facilitates data residency requirements being satisfied by multi-cloud configurations.

By law, the data stored in a cloud infrastructure must reside within a specific geographical region. Matching the cloud storage services and cloud customers before a multi-cloud deployment can be orchestrated reduces latency and ensures compliance with data residency requirements. Multi-cloud services may be formed using diverse cloud providers having different service qualities. Load-balancing across services with varying performance

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

ensures the service level agreement (SLA) of the global service is met. Redundancy in multi-cloud storing services at different cloud service providers in different geographical regions achieves fault-tolerance in data storage. Multi-cloud deployments fulfil jurisdictional laws in all the geographical regions without increasing response time.

Inadvertent data leaks can arise in service requests to external geo-regions. Data in transit must be protected by accessing control and data encryption techniques. Authentication-based access control limits the users of the set of transportation networks from accessing the associated data. Cryptographic-based secret-sharing schemes protect the data from the service providers by storing secret-shares with different service providers. Cryptographic-based bloom filters identify the relevant secret-shares for each user before decryption. Verification-enabled data provenance ensures the correctness of data. Data mounts implementing the above-security modules guarantee that no additional cost is incurred through these processes apart from the cost of service requests. Therefore, privacy-preserving cloud collaboration across geo-regions becomes feasible in practice.

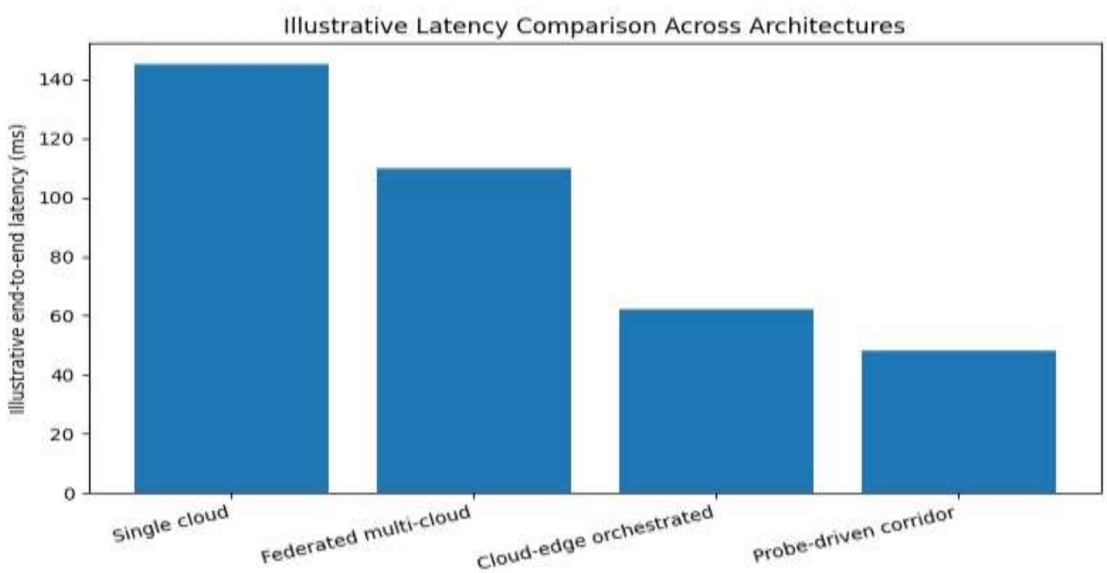
8.1. Compliance in Global Transportation Data Management

Comprehensive and trustworthy data governance frameworks will be essential for enabling real-time decision-making across intertwined transportation networks that span multiple organizational, regional, and national jurisdictions. Policymakers and regulators will be concerned with ensuring that data management in these systems adheres to regulations such as the General Data Protection Regulation (GDPR) in the EU and the Health Insurance Portability and Accountability Act (HIPAA) in the US. These laws delineate boundaries for data processing that providers of public cloud services located in a single jurisdiction must respect. Risk assessments will determine whether potential political, reputational, or financial damage from leakage of sensitive data or non-compliance with laws is tolerable. Provisions for external auditing are inevitably required to confirm that cloud and edge service users in different regions process and exchange data within their respective jurisdictions, thereby avoiding handling of protected data by unauthorized parties.

Transport enterprise and service specifications define data origination and ownership and stipulate privacy and security requirements for all data in motion and in storage. Sensitive data are protected using encryption algorithms whose implementation is specific to the type of transport network in question. Access control mechanisms prevent unauthorized parties from deciphering encrypted data but allow authorized parties to recover both plaintext and secret keys.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

Provenance tracking and accountability measures document data life cycles through a combination of checks and warranties, from data generation by the source transport node to final allocation to the destination transport node. These mechanisms enable conflict-of-interest assertions concerning data usage, thus providing stakeholders with greater confidence in the correctness of decisions made in their local domain in a real-time-deliberative, multi-agent AI system.



Equation 4. Price elasticity derivation

4.1 Price elasticity of demand

Demand as a function of price:

$$Q = Q(P)$$

Elasticity is defined as

$$E_p = \frac{dQ}{dP} \cdot \frac{P}{Q}$$

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

For a linear demand equation

$$Q = \frac{a - P}{b}$$

Differentiate:

$$\frac{dQ}{dP} = -\frac{1}{b}$$

Therefore

$E_p = -\frac{1}{b} \cdot \frac{P}{Q}$ $\boxed{E_p = -\frac{P}{bQ}}$

4.2 Income elasticity

If demand depends on income Y,

$$Q = Q(Y)$$

Then income elasticity is

$$E_Y = \frac{dQ}{dY} \cdot \frac{Y}{Q}$$

If $E_Y > 0$, higher income increases travel demand.

If $E_Y < 0$, the mode behaves like an inferior good.

8.2. Secure Collaboration Across Jurisdictions

Transporting people and goods involves crossing numerous political, economic, and legal borders. Research and real-time applications deal with multiple countries across multiple continents or are deployed with special consideration for the transportation challenges of mega-cities or regions of high geopolitics sensitivity. Privacy and security laws rarely match, and that can be expected in the next few years. Proposals on how the underlying infrastructures of several services can be orchestrated by a third, independent system to fulfil demand and supply in the real world are presented in the literature. In those scenarios, the services possess all required

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

information only when informing transport partners, and all data filtering and validation is performed by the main or monitoring system. In a more complex approach, transit and share-economy systems share with service providers the data necessary for risk analysis or traffic control. But data leaks demand additional layers to secure such collaborations.

Data travelling through banks, storage systems, monitoring services or any other component must be encrypted. Two approaches should be adopted: (1) the data provider encrypts the data before sending, with the proposed sharing or collaboration partners owning the decryption keys, or (2) the service provider encrypts the data using private keys. Control mechanism hubs for sharing and collaborating among transport system partners must also be designed, enabling access control and the signing of transit information by service providers, assigned vehicles, security systems or transit infrastructures. As control mechanisms are deployed on one cloud layer and accessible through APIs, it is possible to create audit trails, monitoring the path taken and people accessing specific pieces of data.

9. Evaluation Methodologies

Simulation-based experimentation and real-world trials guided by a common set of criteria, architectural vision, and global orchestration principles validate the cloud-and-AI orchestration of urban mobility networks and long-haul logistics corridors. Synthetic simulation scenarios with transportation demand models, travel-time distributions, route-choice behavior, service

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

dynamics, data lag, and service quality thresholds calibrate the field-validation benchmarks.

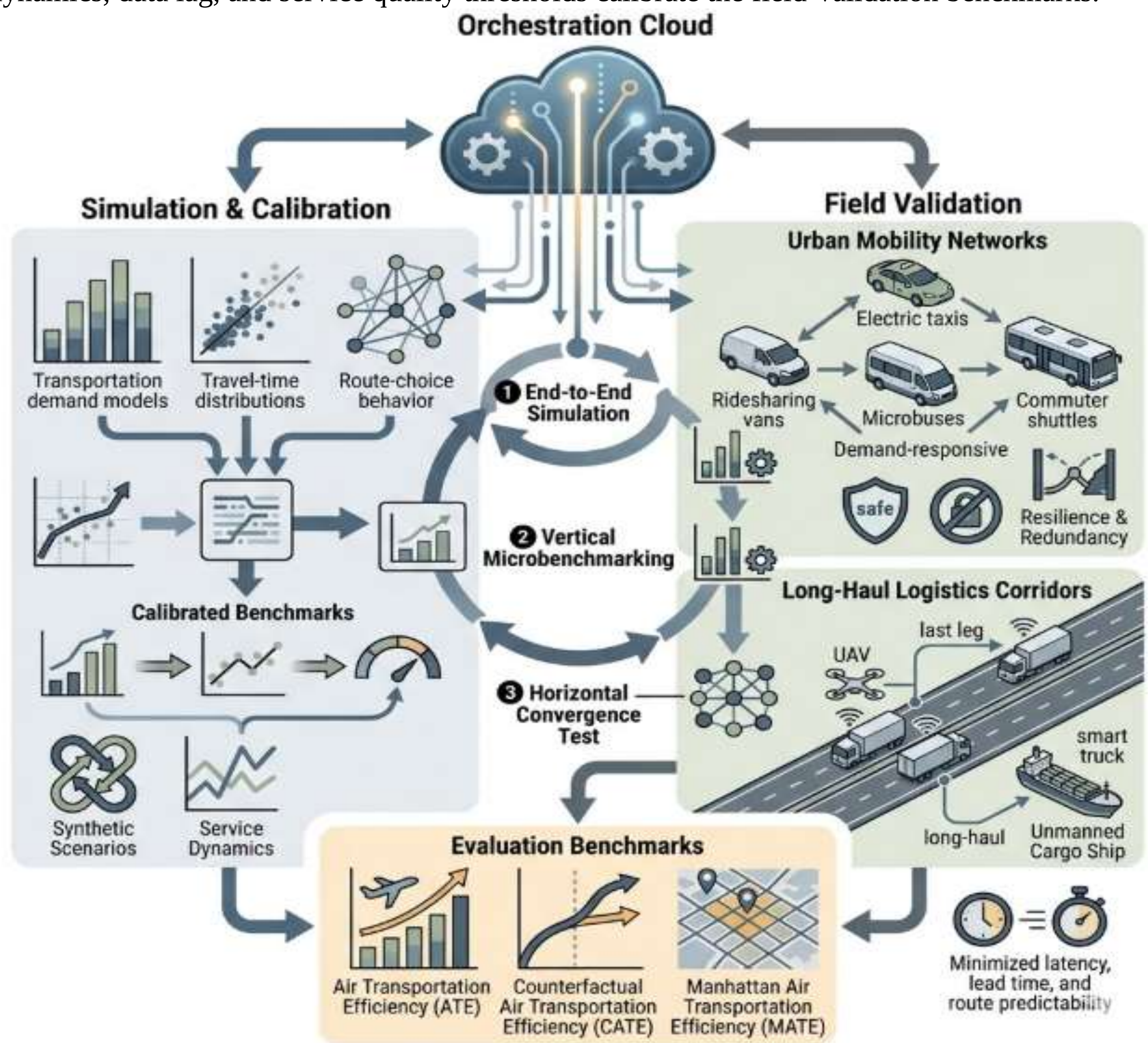


Fig 3: Validated Urban and Corridor Logistics: A Unified Simulation-to-Field Orchestration Framework

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

Comprehensive validation covers an end-to-end simulation, a vertical microbenchmarking of key pipelines, and a horizontal convergence test of the dynamic-traffic-assignment system. The evaluation benchmarks Air Transportation Efficiency (ATE), the Counterfactual Air Transportation Efficiency (CATE), and the Manhattan Air Transportation Efficiency (MATE) metrics.

Urban-mobility networks combine a largely electric fleet of taxis and ridesharing options with a hierarchy of microbuses and commuter shuttles operating under demand-responsive principles. Resilience goals lead to a strong redundancy of supply over demand, allowing for unexpected events such as COVID-19 lockdowns and recovery phases. A multi-hop, multi-carrier-orchestrated freight corridor comprises smart trucks equipped with the full spectrum of automated driving and teleoperations capabilities. The trucks interact with unmanned aerial vehicles (UAVs) and unmanned cargo ships in the last leg and long-haul operations, respectively. Service redundancy serves to alleviate demand peaks while ensuring high service standards in terms of latency, lead time, route-finding, and delivery-time predictability.

9.1. Simulation-Based Validation

Validation of proposed cloud-orchestrated AI systems incorporates dedicated simulation tools for synthetic benchmarking and evaluation, followed by real-world deployment trials using either a testbed or a reduced-scale model. Simulation-based validation is conducted following two sequential steps. First, dedicated simulation scenarios are designed to cover a representative range of likely conditions, choices, externalities, and events. Key performance indicators within these scenarios are defined in relation to the objectives of the underlying cloud-orchestrated AI system(s). Second, multiple runs over these scenarios generate samples of the performance indicators, which are aggregated to quantify the expected performance profiles, including average values, sensitivities to key variables, and ranges of variation.

Synthetic simulation scenarios are constructed for a large number of representative choices and external conditions, such as the overall road demand level, demand patterns—both in relation to origin-destination (OD) pairs and temporal distribution—the presence of public transport, the availability of different transportation modes, and—when a first-come-first-served (FCFS) policy is adopted—traffic congestion levels. The applicability of cloud-based AI systems toward accessibility, affordability, equity, sustainability, and resilience is then explored. Final conclusions reflect on the contributions made and on the conditions required for achieving the desired effects.

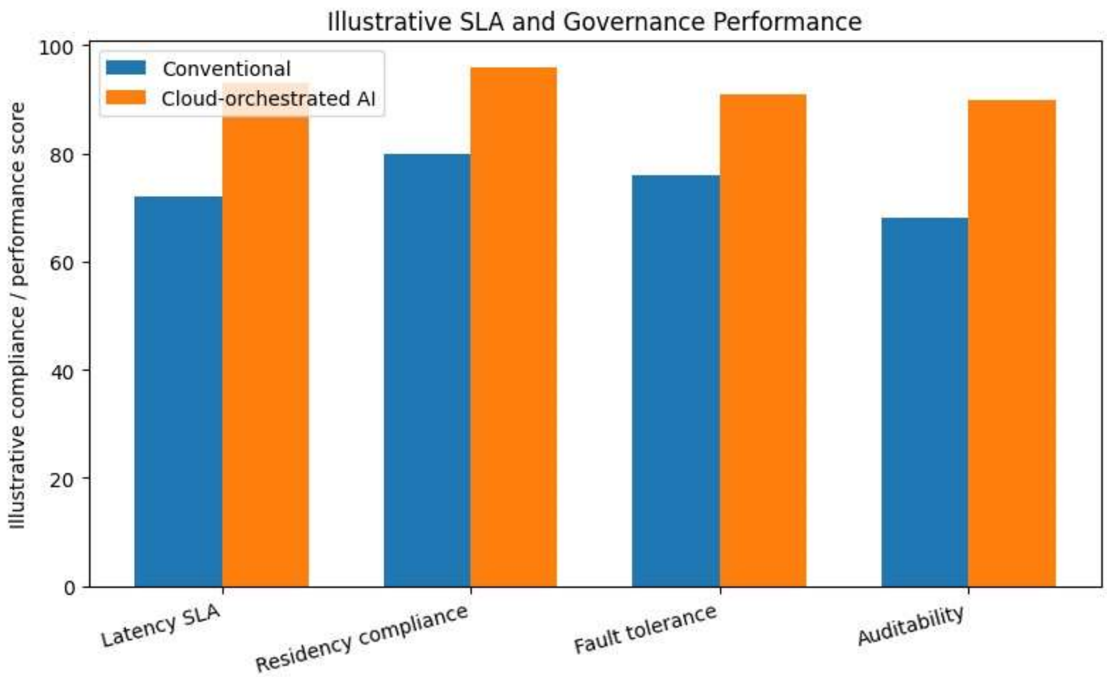
ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

9.2. Field Trials and Pilot Deployments

Field trials enable constrained but realistic deployment of a cloud-operated AI system. They establish a representative configuration, collect system inputs, and benchmark performance. A study thus assesses a regional supply–demand equilibrium and a transportation schedule within three neighbouring countries. Applying the proposed data-pipelines and streaming-analytics processes produces indicators for system validation, including the robustness of machine-learning models.

In contrast, pilot deployments enable cloud-and-edge collaboration within existing operational systems. Experiments are designed to observe the system's ability to improve service uptake while lowering travel times for key user segments across multiple types of clouds. For example, introducing dynamic real-time pricing may increase accessibility for low-income users—supporting the Sustainable Development Goals—although must be undertaken without a significant decrease in affordabilty for mid- and high-income users. Cities may use restoration strategies after sudden infrastructure failures, monitoring the population's natural relocation patterns to enable faster recovery. Traffic-light strategies could validate improvements in travel times and network throughput at various sizeable scales of deployment within shrinking periods, serve as update tests of transportation-type machine-learning approaches, and support the interactive comparison and selection of light co-ordination tables for user applications.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14



10. Deployment Scenarios and Case Studies

Use cases and scenarios for deploying cloud-orchestrated artificial-intelligence systems for real-time optimization of the global transportation network can be grouped based on the primary geographical radius of the substantial transportation flows involved. Some scenarios extend across entire countries, taking advantage of the often-greater resilience that long-distance flows offer under changing demand conditions, while others involve movements and transports on a smaller scale that are determined predominantly by local or regional factors and conditions. Particularly stringent scalability, reliability, and performance requirements—often referred to as "Big City" conditions—arise for the first class of scenario during limited-period high-demand peaks, such as those occurring during large-scale public events.

The first group of scenarios deals with Real-Time Optimization of Cloud-Heavy, Resilient Multi-Cloud AI Systems for Urban Mobility Networks and Cloud-Orchestrated Logistic Updates for Freight and Logistics Corridors. Scalability management and methods for traffic threat detection and alarming are explored for urban mobility networks, while

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

minimization of costs (defined via a multi-criteria approach), detection of dynamic equilibrium between demand and supply of logistics transport capacity, demand-oriented pricing evolution, and assessment of the economic resilience of freight and logistics corridors under geoeconomics constraints are addressed for freight and logistics corridors.

Equation 5. Latency and SLA derivation

Let total end-to-end latency be

$$L_{\text{tot}} = L_{\text{ingest}} + L_{\text{align}} + L_{\text{infer}} + L_{\text{opt}} + L_{\text{dispatch}}$$

To satisfy the SLA:

$$\boxed{L_{\text{tot}} \le L_{\max}}$$

If services are distributed across cloud and edge:

$$L_{\text{tot}} = L_{e\to c} + L_{\text{proc},c} + L_{c\to e} + L_{\text{proc},e}$$

The cloud-edge system is beneficial when

$$L_{\text{tot}}^{\text{cloud-edge}} < L_{\text{tot}}^{\text{single-cloud}}$$

10.1. Urban Mobility Networks

Cloud orchestration of multi-tenant solutions and technologies at the network edge allows service offerings to combine a greater variety of resources, supporting a richer class of applications with better quality of service. The real-time optimization of urban mobility networks showcases these advantages. A cloud-based system dynamically responds to bike-sharing market fluctuations, suggesting rebalancing operations, or to passenger requests and driver availability, proposing ride-sharing opportunities. Pilots for a taxi-hailing service provide routing and scheduling assistance for clusters of vehicles in proximity to similar demand points.

Existing demand-responsive services are typically limited in scope and aggregation, unable to achieve an economic equilibrium in the pricing of ride offers. A new demand–supply market combines elasticity dependencies with real-time monitoring of passenger requests and driver availability. Elasticity assessment guarantees supply fulfilment, while a distributed

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

equilibrium-search mechanism allows timely intervention by the supporting cloud system. Suitable combinations of requests and available rides are identified, contributing to urban traffic sustainability and resilience.

10.2. Freight and Logistics Corridors

Deployment scenarios encompassing freight and logistics corridors open additional avenues of contribution beyond urban mobility networks. Traffic analysis in these domains is primarily infrastructure and planning dependent, with a focus on monitoring trade lane load levels, balance in supply and demand, and conditions for short-term congestion and incident management. Digital twins employed in this context can address dimensioning requirements for new or upgraded infrastructures and assess ATMAs. Nevertheless, under-dimensioning remains a persistent issue, leading to traditional demand management measures.

Four tactical-market mechanisms based on multivariate beta distribution form the basis for future short-term predictions in freight-corridor requirements and in facilitating supply–demand equilibrium through dynamic pricing. The integration of the proposed mechanisms within digital twins constitutes a first step toward improving traffic management in freight corridors. Evaluation of monitoring and market models illustrates intrinsic elasticity properties able to mitigate the inconsistency of induced origin–destination flows. Dynamic pricing closely associated with capacity and load events enables stabilizing short-term demand capture and attractiveness.

Freight corridors connecting main areas of flow experience loading events when prices are discounted, while price increments balance short-term capacity requirements. The resilience properties of the pricing-abstraction model indicate that an ensemble of multivariate beta architectures continuously discovers the best-fit pricing schemas. Resilience remains a problematic notion for markets and is not trivial to define and measure. Nevertheless, multiple dimensions—such as market opening, diversification of suppliers, and market depth—enhance the stability of such mechanisms.

11. Results

Cloud-Orchestrated AI Systems for Real-Time Global Transportation Network Optimization: present a concise, evidence-based academic discussion with formal structure and objective tone.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

Considerable advancements in vehicle and communication technologies are enabling myriads of electrically powered autonomous vehicles to cooperate in a range of transport market segments, from urban mobility to freight and logistics. Such vehicles can jointly operate online in a data-driven fashion that resembles the physical processes of neurons and biological entities in the brain and nature, respectively. However, the supervision support that data-driven Artificial Intelligence may offer to carriers and users in these market segments and the Cyber-Physical Systems and cooperatives that would make best use of it remain largely unexplored. Following the Federated AI paradigm, real-time global optimization of these transport networks should take advantage of Cloud-Edge collaboration due to the high temporal and spatial heterogeneity of the data produced by the respective vehicles. Temporal alignment of the input data generated by the transport and urban infrastructure is critical for its proper exploitation, whether by a single centre or by several centres of expertise. Aligning data from multiple sources, in most cases belonging to different jurisdictions, is a significant challenge, making real-time aggregation for transport network-wide operation difficult.

Four research questions guide the work: What are the benefits of Cloud-Edge collaboration for real-time global multi-modal transport network performance compared with multi-cloud approaches? How can the input data generated by transport infrastructure and vehicles operating in an Urban Mobility Market be aligned for real-time operational exploitation? What Governance Structures and Operating Mechanisms would best enable dynamic Demand–Supply Equilibrium to ensure optimal transport Market conditions? Which Guarantees and Protections are required to ensure network-wide safety and privacy of Data-Driven real-time Autonomous Behaviour of vehicles? Networks with non-overlapping demand-supply can derive advantages from multi-cloud collaboration following high-level service-level agreements. Nevertheless, a probe-driven approach within a Global Transport Corridor would better address real-time data latency constraints of AI-based applications, offering superior performance advantages.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

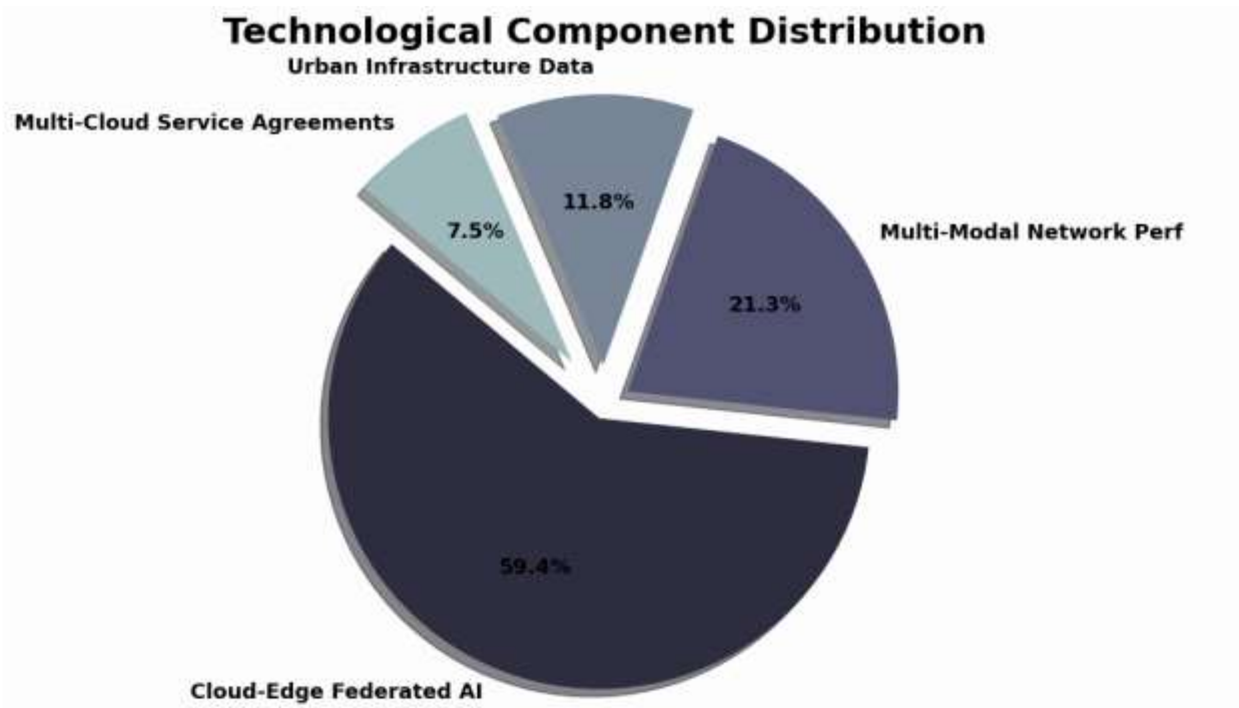


Fig 4: Technological Component Distribution

11.1. Accessibility and Equity in Transportation

Accessibility in transportation encompasses reachability, affordability, and inclusion. It is more than a mere description of the system's "spatial lattice"; it denotes a measure of multiple networks over the same territory. Is it easy, fast, cheap, and otherwise convenient to travel from one place to another on any mode? Is living without a car or working a minority schedule possible? Does freight transport serve the whole society? In the cloud-and-AI-synchronised scenario, many accessibility criteria improve. Demand-supply equilibrium pricing tends to favour car-free persons and those lacking economic power. Inequalities in travels-to-work opportunities have diminished in several cities. Temporal granularity controls balance, and linking income elasticity brings closer the notion of accessibility into equality. In contrast, equity in transport commonly concerns transport injustice: the under-representation of interest- or needs-based voices—women, sex workers, immigrants, and the poor—flows into a "one-size-fits-all" mode choice system.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

Accessibility directs attention towards deficits, often temporally, when ownership and support subsidise operations. The delicate balances within complex, multi-jurisdictional systems equally apply at the network connection level. Individual systems within each urban-rural area must bridge separately, and additional, oversize network width becomes essential and determined—yet these solvers can model this idiom. Insufficient liveness in any proper-mode transport network transmits and concentrates into the whole-network adequacy. "Supply chains" ponder the ability of loads to trans-ride a whole nation accurately, reliably, and within plan. Where insurance and insurance companies, and freight agents, still exert poor similes for congruence, logistics corridors and trade corridors prenotify available freight capacity, or allocator-at-a-distance capacities, low congestion levels, stable transfer time, and predictably fair rates.

11.2. Accountability for Autonomous Decisions

Adverse social repercussions of autonomous behavior in safety-critical systems, such as biased traffic enforcement, have drawn increasing attention. The importance of auditability, traceability, and accountability for transportation-oriented AI actors has been highlighted. An audit and governance mechanics framework for transportation-oriented federated AI systems is proposed, supported by a theoretical examination of admissibility for decisions based on real-time demand–supply equilibrium combined with a dynamic-pricing policy that fulfills the Wyne–Mandelker condition for market stability. Empirical validation is given through monitoring model outcomes, focusing on produced data and associated effects with social repercussions. Transportation networks, both urban and freight, are identified as an appropriate testbed given the swift integration of policy-based actions from simulation systems into operation. Research directions for adding guarantees of fairness and equity to salient public or private actors are outlined.

The congruence of semantic provenance with the general cargo of critical auditability promotes a further discussion of the relation between a minimal governance structure and the auditability of autonomous behaviors in transportation networks. This intersection indicates that a provenance language supporting diversified but well-constrained auditability conditions is of paramount importance in transportation-oriented federated AI systems. With auditing and assurance—an absolute necessity for safety-critical systems like urban mobility networks—still in a mere exploratory stage, it is anticipated that refinements of the proposed evaluation toolbox will contribute to the community's research efforts in this field.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

12. Conclusion

Cloud orchestrated AI systems promised improved situational awareness and real-time coordination for networked mobility and logistics operations across jurisdictional boundaries. By harmonizing the approach adopted at the node level, they aligned objectives and scales, enabling aggregate control. Federated edge-cloud and edge-edge coordination mechanisms simplified data residency compliance and facilitated multi-source data fusion while outsourcing open-ended processing tasks. Multi-cloud and edge-cloud collaboration through data-value exchange agreements was demonstrated. Together, these elements supported large-scale synthetic and pilot deployments addressing the expanding needs of networked mobility and logistics, and infrastructure that operated effectively within the laws and regulation governing deployment environments.

The dynamic nature of demand and supply in urban mobility networks challenged accessibility and equity, raising questions around safety, reliability, fairness, acceptability and accountability of decision support systems. Real-time data alignment addressed temporal integrity thus supporting market and pricing mechanisms for demand-supply equilibrium and fairness, but also inter-domain equity within a federated cloud model without a single point of control or failure. Consolidated audit information trail for market transactions within defined regulatory boundaries assured accountability despite the autonomous nature of price-setting policies.

References

1. Bogaerts, T., Masegosa, A. D., Angarita-Zapata, J. S., Onieva, E., & Hellinckx, P. (2020). A graph CNN-LSTM neural network for short and long-term traffic forecasting based on trajectory data. Transportation Research Part C: Emerging Technologies, 112, 62–77.
2. Yu, B., Lee, Y., & Sohn, K. (2020). Forecasting road traffic speeds by considering area-wide spatio-temporal dependencies based on a graph convolutional neural network (GCN). Transportation Research Part C: Emerging Technologies, 114, 189–204.
3. Kumar, M. V. K., Kolla, S. H., Pamisetty, V., Pandiri, L., Yandamuri, U. S., & Valiki, D. (2026). Enterprise-Scale Generative AI Agents for Secure and Governed Automation in Insurance and Public Financial Management. In 2026 International Conference on Computational Robotics, Testing and Engineering Evaluation (ICCRTEE) (pp. 1–6). IEEE. 2026 International Conference on Computational Robotics, Testing and Engineering Evaluation (ICCRTEE). https://doi.org/10.1109/iccrtee68719.2026.11566439

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

4. Cui, Z., Lin, L., Pu, Z., & Wang, Y. (2020). Graph Markov network for traffic forecasting with missing data. Transportation Research Part C: Emerging Technologies, 117, 102671.
5. Pan, Z., Liang, Y., Wang, W., Yu, Y., Zheng, Y., & Zhang, J. (2020). Urban traffic prediction from spatio-temporal data using deep meta learning. Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 1928–1936.
6. Wu, Z., Pan, S., Long, G., Jiang, J., Chang, X., & Zhang, C. (2020). Connecting the dots: Multivariate time series forecasting with graph neural networks. Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 753–763.
7. Kumar, S. S., Garapati, R. S., Segireddy, A. R., Kalisetty, S., Inala, R., & Nagabhyru, K. C. (2026). Hybrid Deep Neural Network–DevOps Pipeline Optimization for Risk Prediction in Cloud-Native Workers' Compensation Platforms. In 2026 IEEE International Conference for Convergence in Computing Technology (I3CTCON) (pp. 1–6). IEEE. 2026 IEEE International Conference for Convergence in Computing Technology (I3CTCON). https://doi.org/10.1109/i3ctcon68242.2026.11507219
8. Zheng, C., Fan, X., Wang, C., & Qi, J. (2020). GMAN: A graph multi-attention network for traffic prediction. Proceedings of the AAAI Conference on Artificial Intelligence, 34(1), 1234–1241.
9. Wang, X., Ma, Y., Wang, Y., Jin, W., Wang, X., Tang, J., Jia, C., & Yu, J. (2020). Traffic flow prediction via spatial temporal graph neural network. Proceedings of The Web Conference 2020, 1082–1092.
10. Radha, S., Gottimukkala, V. R. R., Thottara, S., Vandhana, K., & J, Gokulraj. (2025). Adaptive Video Streaming Over 5G Networks Using Deep Reinforcement Learning with Closed-Loop Feedback Mechanism for Bitrate Control. In 2025 International Conference on Communication, Computer, and Information Technology (IC3IT) (pp. 1–6). IEEE. 2025 International Conference on Communication, Computer, and Information Technology (IC3IT). https://doi.org/10.1109/ic3it66137.2025.11341184
11. Tedjopurnomo, D. A., Bao, Z., Zheng, B., Choudhury, F. M., & Qin, A. K. (2020). A survey on modern deep neural network for traffic prediction: Trends, methods and challenges. IEEE Transactions on Knowledge and Data Engineering, 34(4), 1544–1561.
12. Maas, T., & Bloem, P. (2020). Uncertainty intervals for graph-based spatio-temporal traffic prediction. arXiv preprint arXiv:2012.05207.
13. Qin, Z. T., Tang, X., Jiao, Y., Zhang, F., Xu, Z., Zhu, H., & Ye, J. (2020). Ride-hailing order dispatching at DiDi via reinforcement learning. INFORMS Journal on Applied Analytics, 50(5), 272–286.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

14. Inala, R., Sheelam, G. K., Aitha, A. R., Lakshmi, A. U., Nagabhyru, K. C., & Segireddy, A. R. (2026). Architecting Hybrid Data Products Using AI/ML and Agentic AI for Group Insurance and Retirement Solution Platforms with Advanced Data Governance. In 2026 IEEE International Conference on AI Engineering and Innovations (AIEI) (pp. 1–6). IEEE. 2026 IEEE International Conference on AI Engineering and Innovations (AIEI). https://doi.org/10.1109/aiei69164.2026.11497971
15. Feng, J., Gluzman, M., & Dai, J. G. (2020). Scalable deep reinforcement learning for ride-hailing. arXiv preprint arXiv:2009.14679.
16. Ren, S., Li, Q., Zhang, L., Qin, Z., & Yang, B. (2020). Optimising stochastic routing for taxi fleets with model enhanced reinforcement learning. arXiv preprint arXiv:2010.11738.
17. Danghi, P. S., Maniraj, K., Jain, P., Adilakshmi, K., Garapati, R. S., & Jain, S. K. (2025). Artificial Intelligence Based Energy Optimization Framework for Wireless Sensor Networks. In 2025 IEEE 5th International Conference on ICT in Business Industry & Government (ICTBIG) (pp. 1–6). IEEE. 2025 IEEE 5th International Conference on ICT in Business Industry & Government (ICTBIG). https://doi.org/10.1109/ictbig68706.2025.11323860
18. Li, Z., Yu, H., Zhang, G., Dong, S., & Xu, C.-Z. (2021). Network-wide traffic signal control optimization using a multi-agent deep reinforcement learning. Transportation Research Part C: Emerging Technologies, 125, 103059.
19. Yoon, J., Ahn, K., Park, J., & Yeo, H. (2021). Transferable traffic signal control: Reinforcement learning with graph centric state representation. Transportation Research Part C: Emerging Technologies, 130, 103321.
20. Reddy, M. S. R. L., Sunitha, T., Kanchana, K., Nagubandi, A. R., Segireddy, A. R., & Bhavanam, S. N. (2026). AI-Enhanced Blockchain Consensus Mechanisms for Secure Transaction Validation. In 2026 International Conference on Emerging Research in Smart Electronics and Machine Informatics (ECMI) (pp. 1–11). IEEE. 2026 International Conference on Emerging Research in Smart Electronics and Machine Informatics (ECMI). https://doi.org/10.1109/ecmi68341.2026.11602724
21. Wang, T., Cao, J., & Hussain, A. (2021). Adaptive traffic signal control for large-scale scenario with cooperative group-based multi-agent reinforcement learning. Transportation Research Part C: Emerging Technologies, 125, 103046.
22. Li, F., Feng, J., Yan, H., Jin, G., Jin, D., & Li, Y. (2021). Dynamic graph convolutional recurrent network for traffic prediction: Benchmark and solution. arXiv preprint arXiv:2104.14917.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

23. Kumar, S. S., Garapati, R. S., Segireddy, A. R., Kalisetty, S., Inala, R., & Nagabhyru, K. C. (2026). Hybrid Deep Neural Network–DevOps Pipeline Optimization for Risk Prediction in Cloud-Native Workers' Compensation Platforms. In 2026 IEEE International Conference for Convergence in Computing Technology (I3CTCON) (pp. 1–6). IEEE. 2026 IEEE International Conference for Convergence in Computing Technology (I3CTCON). https://doi.org/10.1109/i3ctcon68242.2026.11507219
24. Li, M., & Zhu, Z. (2021). Spatial-temporal fusion graph neural networks for traffic flow forecasting. Proceedings of the AAAI Conference on Artificial Intelligence, 35(5), 4189–4196.
25. Fang, Z., Long, Q., Song, G., & Xie, K. (2021). Spatial-temporal graph ODE networks for traffic flow forecasting. Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, 364–373.
26. Thutari, R. T., Garapati, R. S., B M, Manjula., R K, Supriya., & M, Senbagan. (2025). Adaptive Access Control and Authentication Management for IoT Using Attention-GRU and Reinforcement Learning. In 2025 2nd International Conference on Software, Systems and Information Technology (SSITCON) (pp. 1–6). IEEE. 2025 2nd International Conference on Software, Systems and Information Technology (SSITCON). https://doi.org/10.1109/ssitcon66133.2025.11342003
27. Jiao, Y., Tang, X., Qin, Z. T., Li, S., Zhang, F., Zhu, H., & Ye, J. (2021). Real-world ride-hailing vehicle repositioning using deep reinforcement learning. Transportation Research Part C: Emerging Technologies, 130, 103289.
28. Sun, J., & Kim, J. (2021). Joint prediction of next location and travel time from urban vehicle trajectories using long short-term memory neural networks. Transportation Research Part C: Emerging Technologies, 128, 103114.
29. Kumar, N., & Raubal, M. (2021). Applications of deep learning in congestion detection, prediction and alleviation: A survey. Transportation Research Part C: Emerging Technologies, 133, 103432.
30. Baladari, V., Nagubandi, A. R., Charan Teja Tadi, S. R. C., Selvi, A. T., Sreedevi, V., & Nithya, M. (2026). Predictive AI Model for Financial Risk Assessment in Dynamic Market Environments. In 2026 International Conference on Communication, Computing and Emerging Technologies (IC3ET) (pp. 748–753). IEEE. 2026 International Conference on Communication, Computing and Emerging Technologies (IC3ET). https://doi.org/10.1109/ic3et64989.2026.11467452

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

31. Xu, D., Wei, X., & Li, Y. (2021). A flexible deep learning-aware framework for travel time prediction considering traffic event. Engineering Applications of Artificial Intelligence, 106, 104491.
32. Chen, C., Zhang, Y., & Wang, H. (2022). Data efficient reinforcement learning and adaptive optimal perimeter control of network traffic dynamics. Transportation Research Part C: Emerging Technologies, 142, 103759.
33. Noaeen, M., Naik, A., Goodman, L., Crebo, J., Abrar, T., Shakeri Hossein Abad, Z., Bazzan, A. L. C., & Far, B. (2022). Reinforcement learning in urban network traffic signal control: A systematic literature review. Expert Systems with Applications, 199, 116830.
34. Garapati, R. S., Paleti, S., Meda, R., Nagabhyru, K. C., & Deepa Priya, B. S. (2026). Physical-Unclonable-Function-Based Secure and Anonymous User Authentication for Smart Homes. In Lecture Notes in Electrical Engineering (pp. 367–378). Springer Nature Switzerland. https://doi.org/10.1007/978-3-032-20235-2_33
35. Qin, Z. (Tony), Zhu, H., & Ye, J. (2022). Reinforcement learning for ridesharing: An extended survey. Transportation Research Part C: Emerging Technologies, 144, 103852.
36. Liu, Y., Wu, F., Lyu, C., Li, S., Ye, J., & Qu, X. (2022). Deep dispatching: A deep reinforcement learning approach for vehicle dispatching on online ride-hailing platform. Transportation Research Part E: Logistics and Transportation Review, 161, 102694.
37. Long, M., Zou, X., Zhou, Y., & Chung, E. (2022). Deep reinforcement learning for transit signal priority in a connected environment. Transportation Research Part C: Emerging Technologies, 142, 103814.
38. Inala, Ramesh, Ravi Shankar Garapati, Avinash Reddy Aitha, Venkata Bhardwaj Komaragiri, Vijaya Rama Raju Gottimukkala, Mahesh Recharla, Pallav Kumar Kaulwar et al. "Ai-driven adaptive meta-learning framework for self-evolving neural architecture optimization." U.S. Patent Application 19/389,108, filed March 12, 2026.
39. Shaygan, M., Meese, C., Li, W., Zhao, X. G., & Nejad, M. (2022). Traffic prediction using artificial intelligence: Review of recent advances and emerging opportunities. Transportation Research Part C: Emerging Technologies, 145, 103921.
40. Pereira, M., Lang, A., & Kulcsár, B. (2022). Short-term traffic prediction using physics-aware neural networks. Transportation Research Part C: Emerging Technologies, 142, 103772.
41. Choi, J., Choi, H., Hwang, J., & Park, N. (2022). Graph neural controlled differential equations for traffic forecasting. Proceedings of the AAAI Conference on Artificial Intelligence, 36(6), 6367–6374.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

42. Davuluri, P. S. L. (2023). AI-Augmented Sanctions Screening: Enhancing Accuracy and Latency in Real Time Compliance Systems. AI-Augmented Sanctions Screening: Enhancing Accuracy and Latency in Real Time Compliance Systems (December 15, 2023).
43. Zhang, T., Cheng, J., & Zou, Y. (2024). Multimodal transportation routing optimization based on multi-objective Q-learning under time uncertainty. Complex & Intelligent Systems, 10, 3133–3152.
44. Li, D., Zhu, F., Wu, J., Wong, Y. D., & Chen, T. (2024). Managing mixed traffic at signalized intersections: An adaptive signal control and CAV coordination system based on deep reinforcement learning. Expert Systems with Applications, 238, 121959.
45. Cai, C., & Wei, M. (2024). Adaptive urban traffic signal control based on enhanced deep reinforcement learning. Scientific Reports, 14, 14116.
46. Agarwal, A., Sahu, D., Mohata, R., Jeengar, K., Nautiyal, A., & Saxena, D. K. (2024). Dynamic traffic signal control for heterogeneous traffic conditions using Max Pressure and reinforcement learning. Expert Systems with Applications, 254, 124416.
47. Han, G., Liu, X., Wang, H., Dong, C., & Han, Y. (2024). An attention reinforcement learning–based strategy for large-scale adaptive traffic signal control system. Journal of Transportation Engineering, Part A: Systems, 150(3).
48. Kim, Y., Tak, H.-Y., Kim, S., & Yeo, H. (2024). A hybrid approach of traffic simulation and machine learning techniques for enhancing real-time traffic prediction. Transportation Research Part C: Emerging Technologies, 160, 104490.
49. Chen, K., Liang, Y., Han, J., Feng, S., Zhu, M., & Yang, H. (2024). Semantic-fused multi-granularity cross-city traffic prediction. Transportation Research Part C: Emerging Technologies, 162, 104604.
50. Kalita, T., Prasad Tiwari, S., Reddy Aitha, A., & Garg, A. (2026). Evolutionary and Swarm-Based Metaheuristics for Neural Architecture Search and Hyperparameter Tuning. Available at SSRN 6708638.
51. Sengupta, A., Mondal, S., Das, A., & Guler, S. I. (2024). A Bayesian approach to quantifying uncertainties and improving generalizability in traffic prediction models. Transportation Research Part C: Emerging Technologies, 162, 104585.
52. Ma, Y., Lou, H., Yan, M., Sun, F., & Li, G. (2024). Spatio-temporal fusion graph convolutional network for traffic flow forecasting. Information Fusion, 104, 102196.
53. Xu, T., Deng, J., Ma, R., Zhang, Z., Zhao, Y., Zhao, Z., & Zhang, J. (2024). Hierarchical spatio-temporal graph ODE networks for traffic forecasting. Information Fusion, 102614.

ISSN: 3067-4190
JOURNAL OF ARTIFICIAL INTELLIGENCE AND BIG DATA DISCIPLINES
Volume: 04 Issue: 02
RECEIVED: APRIL 28 REVISED: MAY 11 ACCEPTED: MAY 23 PUBLISHED: JUNE 14

54. Khalesian, M., Furno, A., & Leclercq, L. (2024). Improving deep-learning methods for area-based traffic demand prediction via hierarchical reconciliation. Transportation Research Part C: Emerging Technologies, 159, 104410.
55. Bharathi, D., González Sopeña, J. M., Clarke, S., & Ghosh, B. (2024). Travel time prediction utilizing hybrid deep learning models. Transportation Research Record, 2678(4), 56–65.
56. Yu, J., Laharotte, P.-A., Han, Y., & Leclercq, L. (2023). Decentralized signal control for multi-modal traffic network: A deep reinforcement learning approach. Transportation Research Part C: Emerging Technologies, 154, 104281.
57. Rahman, R., & Hasan, S. (2023). A deep learning approach for network-wide dynamic traffic prediction during hurricane evacuation. Transportation Research Part C: Emerging Technologies, 152, 104126.
58. Li, M., & Zhu, Z. (2023). A macro–micro spatio-temporal neural network for traffic prediction. Transportation Research Part C: Emerging Technologies, 156, 104331.
59. Shen, W., Zou, L., Deng, R., Wu, H., & Wu, J. (2023). A bus signal priority control method based on deep reinforcement learning. Applied Sciences, 13(11), 6772.
60. Ghandeharioun, Z., Zendehdel Nobari, P., & Wu, W. (2023). Exploring deep learning approaches for short-term passenger demand prediction. Data Science for Transportation, 5, Article 19.
61. Bharathi, D., González Sopeña, J. M., Clarke, S., & Ghosh, B. (2023). Travel time prediction utilizing hybrid deep learning models. Transportation Research Record.
62. Shao, J., Li, S., Zhang, K., Wang, A., & Li, M. (2025). Cross-city traffic prediction based on deep domain adaptive transfer learning. Transportation Research Part C: Emerging Technologies, 176, 105152.
63. Ke, Z., Zou, Q., Liu, J., & Qian, S. (2025). Real-time system optimal traffic routing under uncertainties—Can physics models boost reinforcement learning? Transportation Research Part C: Emerging Technologies, 173, 105040.