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Cloud-Enabled Artificial Intelligence for Predictive Traffic Management and Urban Sustainability in Smart Cities

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Abstract: Urban mobility is a major concern for large metropolitan areas. Cloud-enabled Artificial Intelligence (AI) technology may help to manage travel demand and offer a more sustainable urban mobility model for smart cities. An AI-driven, cloud-enabled architectural framework applied to traffic management and control business processes is proposed. It integrates four AI-based predictive models with real-time traffic control and incident-response systems. Different data-driven use cases, proved in two metropolitan areas, illustrate the applicability of this framework in real operational environments. Results show that this approach is capable of managing urban traffic in real time. In addition, it demonstrates how AI-based models can be developed, deployed, and operated within cloud environments, offering a decision-support capability.

The central role of predictive traffic management systems in the cloud-enabled AI model for smart cities is assessed. Demand management processes and the integration of Mobility-as-a-Service platforms are also analyzed. These are mandatory steps to offer a sustainable traffic model for large metropolitan areas. Finally, other aspects such as environmental protection and energy consumption in urban mobility are examined. Traffic management by predictive systems enables a more accurate confrontation of real traffic conditions, improving the energy, environmental, and resilience contexts.

Keywords: Smart City Traffic Management, Cloud-Enabled Artificial Intelligence, AI-Driven Urban Mobility, Predictive Traffic Management Systems, Real-Time Traffic Control, Intelligent Incident Response, Urban Demand Management, Mobility-as-a-Service (MaaS), Cloud-Based Decision Support Systems, Data-Driven Traffic Optimization, Sustainable Urban Mobility Models, Metropolitan Traffic Analytics, AI Deployment in Cloud Environments, Traffic Prediction Models, Smart Transportation Architectures, Energy-Efficient Urban Mobility, Environmental Impact Reduction, Resilient Transportation Systems, Integrated Traffic Control Frameworks, AI-Enabled Smart Cities.

1.INTRODUCTION

Motorized mobility plays a prominent role in the economic development of humanity, but with serious consequences that question its sustainability. The trade-offs and conflicts between motorized mobility, social equity, and the environment are the biggest challenges of modern societies. The advent of Smart Cities introduces advanced technologies capable of inducing safer and more efficient traffic operation, and consequently cleaner urban environments. Cloud computing enables the deployment of data-intensive applications and broad data storage, opening new possibilities for managing mobility. A promising research direction lies in deploying Artificial Intelligence (AI) in the Cloud to predict a wide range of mobility phenomena and enable various Traffic Management Systems (TMS) that require slightly varied characteristics.

Cloud computing and AI are now being successfully implemented in several domains, including traffic prediction and management. Nevertheless, systematic studies assessing the main implementations, advantages, and drawbacks of these technologies for real-time traffic control, incident management, demand management, and more are still incipient. A detailed analysis enables a better understanding of the technology, fills existing knowledge gaps, and indicates future research directions.

1.1. Background and Context

Cloud computing is a pivotal enabling technology for smart cities, offering scalable distributed networks and hosting platforms for Internet of Things (IoT) devices. Cloud services deployed outside city boundaries allow for the dedicated

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use of specialized resources and capabilities. Traffic management is one of the first domains to leverage cloud-enabled Artificial Intelligence (AI) for predictive decision making over travel demand.
For sufficiently large metropolitan areas, cloud-use allows real-time, network-wide traffic control in response to demand signals from motorists. Decision-making operates at longer time scales, district-wide, and involves a mix of economic incentives and pricing/routing guidance. Predictive AI models provide the required travel demand across the city for these decision tasks. Demand management offers a way to provide predictable and controllable levels of demand to the network while minimizing costs, adversely affecting network users as little as possible, and interfacing seamlessly with public transport systems.
Building on two decades of improvements in mobile and sensor technologies, a wealth of real-time, heterogeneous data on urban dynamics is now available within cities. However, data quality, volume, diversity, and reliability are often insufficient for effective exploitation. Analytics and predictive models are therefore deployed in the cloud, integrating, processing, and combining diverse data sources to replicate data assets usually require for efficient network decision-making.

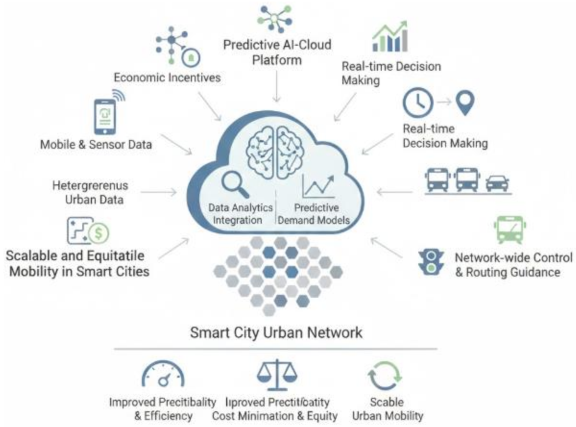

Fig 1: Adaptive Urban Governance: Cloud-Enabled AI for Predictive Demand Management and Integrated Traffic Control

2. THEORETICAL FOUNDATIONS

While traditional machine learning methods provide reliable predictions, the integration of deep learning frameworks is emerging as the new frontier owing to their superior performance. AI-based predictions for the next few minutes (temporal prediction) allow for real-time control and are particularly beneficial for direction-specific traffic management, such as traffic light control or lane management. Since traffic predictions are intricately connected with many other planning and management issues, numerous prediction models and methods have been developed with varying prediction horizons, target variables, and prediction scopes.
Conversely, temporal predictions for the next few hours are useful when the integrated information is necessary but where the time requirement for fast-response decisions does not permit operation-specific model integration (e.g., incident response). Traffic issues can also be addressed by location-specific prediction models. However, the scope of correct decisions is often limited, leading to the development of demand management and Mobility-as-a-Service systems that use traffic predictions at longer horizons for pricing and routing decision integration. These mobility supply and demand management systems also minimize the need for real-time control by optimizing mode and route choice decisions across various transport modes before travel and their actual choices during travel.

2.1. Cloud Computing and Edge-Cloud Architectures

As urban mobility systems become increasingly complex, cloud-enabled Artificial Intelligence (AI) offers innovative technical solutions for real-time predictive traffic management. Based on a hybrid edge-cloud architecture, these systems centralise data analysis and modelling tasks in the cloud while employing a geographically-distributed data sensor network to serve latency-sensitive applications and near real-time response needs. The potential of cloud-enabled AI for

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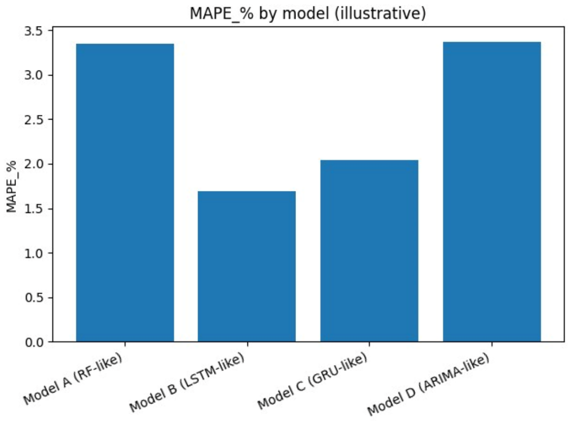
predictive traffic control, traffic-demand management, incident management, and Mobility as a Service is demonstrated through a series of case studies in a metropolitan area.

Cloud Computing

Cloud computing is generally understood as a model for ubiquitous and convenient access to shared pools of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction. Resources are made available by a service provider through a set of scalable services, such as IaaS, PaaS, or SaaS. Technically, cloud computing can be deconstructed into scalable processing, storage and network components that are interconnected by virtualised, low-latency links. These components are consolidated into large datacentres and made accessible to a large number of external customers. Large-scale cloud systems represent the next stage in the evolution of data centres, clusters and grid computing that have been experimentally explored in the past decades. These systems harness the tremendous growth in Internet bandwidth and provide economically attractive solutions for scalable, parallel processing and large-scale data storage.



Equation A. MAPE (Mean Absolute Percentage Error) — full derivation

Goal: error expressed as a percentage of the true value (scale-free).

Step 1: Start from absolute error

$$|y_t - \hat{y}_t|$$

Step 2: Convert to relative error by dividing by true value

$$\left|\frac{y_t - \hat{y}_t}{y_t}\right|$$

(Requires $y_t \neq 0$; if y_t can be near zero, practitioners often use sMAPE or add an ϵ.)

Step 3: Average over all time points and convert to percent

$$\mathrm{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right|$$

2.2. Artificial Intelligence for Traffic Prediction

Artificial Intelligence (AI) algorithms can yield traffic predictions. AI encompasses methods designed “to emulate traits of human intelligence” by using intelligent agents. Abundant data on past traffic patterns enable the development of AI models, which learn to generalize input-output relationships so they can provide predictions on unseen data points. The traffic data that underpin learning are often considered “big data” because of their volume, variety, velocity, and veracity.

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The AI model must be chosen to suit the features, labels, and amount of training data, while ensuring that an accurate model is generated within an acceptable time. The features selected for prediction can include recent traffic conditions, day of the week, season, significant events, road work, historical traffic data, and external data such as weather conditions, public holidays, and school events. The performance of the AI model can be evaluated with extra data not used for training, and complementary validation can be performed across different locations and temporal conditions.

3. METHODOLOGICAL FRAMEWORK

The methodological framework encompasses two interrelated aspects. The data ecosystem defines the different data sources and models, data types, spatiotemporal data quality, interoperability, and the management of data for traffic prediction. Integrating multi-source data from real-time sensors requires a pragmatic approach to deal with different spatiotemporal resolutions and data quality issues. The proposed predictive modeling techniques detail the steps for facilitating the identification of traffic demand and supply that affect urban mobility services. Preprocessing data for predictive model training and validation is designed for detecting spatiotemporal resolution and model type. The combination of predictors with dedicated learning models aim to optimize the predictive performance.

Traffic prediction relies on future traffic demand in space and time and can be represented as prediction for each individual road segment at fixed time intervals in the specific future period. Predictive models can be considered for each control loop and decision horizon of the Traffic Control Centre. Different drivers steer traffic in the urban area: Private Cars belong to residents and passers in the area, Taxies have a demand for short-distance routes, Buses have a demand with long-distance and high-frequency service, and Others are also passing through but have no stops in the area. Relevant features include categories of roads in the urban area, spatial and temporal records of overall road traffic, records of Keyword Searching in major Search Engines, records of price adjustment of Taxies, and records of plans of any temporary road closure and speed limit adjustment. The model performance is evaluated based on three metrics (MAE, RMSE, MAPE) and cross-validation, and the predictive results are validated by prediction against the actual records.

Model	MAE	RMSE	MAPE_%
Model A (RF-like)	26.697005099565498	31.461153181123784	3.3537902721301407
Model B (LSTM-like)	13.361494765978534	17.206423647929107	1.6861626567638874
Model C (GRU-like)	16.04637655631512	20.34735442674958	2.0366754643758704
Model D (ARIMA-like)	26.694544698192704	33.45579275418808	3.372344818884845

3.1. Data Ecosystem and Sensor Integration

A data ecosystem integrating heterogeneous traffic sensors and sources is required to enable predictive traffic management at the metropolitan scale. Many types of data are useful, including real-time vehicular flows, positions, and speeds, historical patterns, and weather forecasts. Data quality and availability therefore condition the predictive modeling pipelines, while the integration of urban and transport data ecosystem supports complete and multimodal predictive models.

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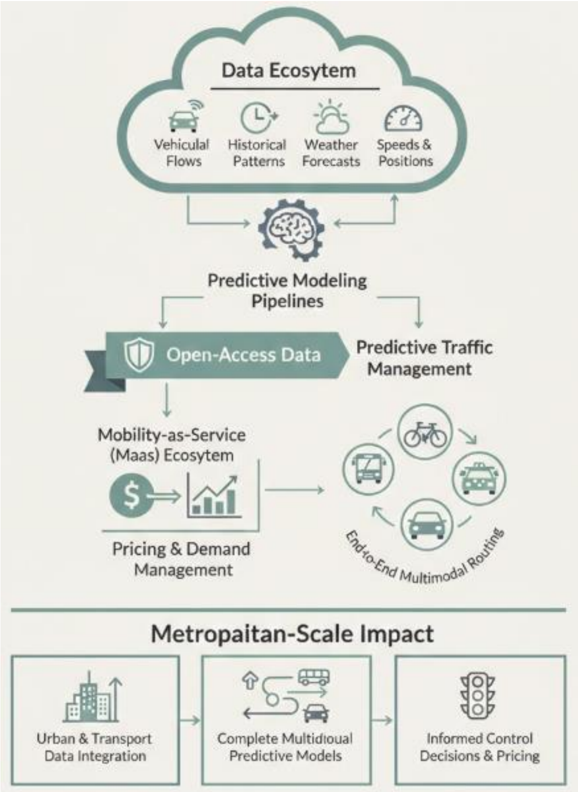

Fig 2: Integrated Data Ecosystems for Metropolitan Predictive Traffic Management: A Multimodal Framework for Open-Access Mobility-as-a-Service (MaaS) and Dynamic Demand Pricing

The open-access nature of the data is also critical. Control decisions based on predicted traffic conditions can significantly benefit from the establishment of a real-time mobility-as-a-service ecosystem providing end-to-end multimodal routing across public transport, shared services, bicycles, and taxis. By supplying the predicted traffic conditions to a complete-multimodal routing engine, demand management pricing schemes that establish the relation between the demand for urban mobility and the supply can be evaluated. Therefore, pricing and routing are linked to the traffic conditions obtained from the predictive traffic-management framework.

3.2. Predictive Modeling Techniques

The investigation of traffic prediction across multiple temporal horizons focuses on enablers such as supervised ML and DL approaches. To this end, a set of prediction models is trained with traffic data at several spatial scales and prediction horizons and is tuned for multiple metrics. The models are trained on historical data covering the COVID-19 lockdown period, during which a significant drop in mobility was observed, and, therefore, validated with data from the period after the lockdowns, characterized by a return of demand for movements. Data preprocessing and model hyperparameterization are carried out with a nested structure. An extensive set of criteria is used to evaluate and select the models, including performance during training (minimization of the error between predicted and observed values), variance (robustness), and bias (detection of a systematic over- or underestimation).

In addition to the data set used for training, the selected models must also be predictive for the forthcoming models, validated on data from a different period and, particularly, when the mobility profile is different from the training data, thus reflecting a capacity for generalization. The selection of predictive models is based on an analysis of an extensive set of metrics, namely, accuracy (the share of correct predictions); direction accuracy (the share of values predicted with the correct sign), mean absolute error, and Q6 efficiency index (comparison of predictions with a simple persistence model); and F1 score and HSS (both for classification models). This not only ensures the identification of models with acceptable prediction performance but also the selection of models with complementary error profiles, thus allowing a more suitable model ensemble to be built for the final multi-modal supply and demand synthesis.

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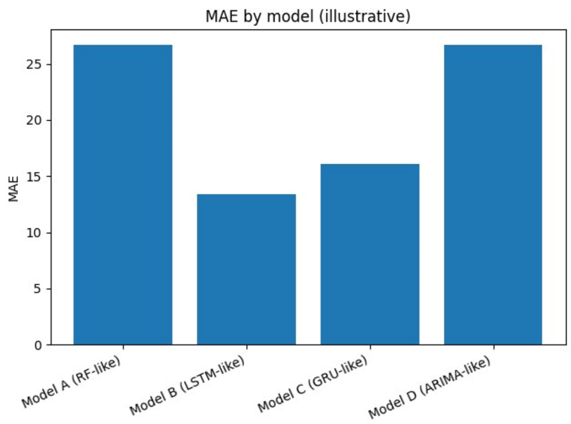
4. CLOUD-ENABLED TRAFFIC MANAGEMENT SYSTEMS

Cloud-enabled urban mobility systems provide a shared platform for traffic control, demand management, and Mobility as a Service applications. A city cloud maintains high-level real-time traffic information and automates incident detection and response. Structural, performance, and communication automation can close real-time traffic control loops, while decision-node located traffic prediction can meet real-time data latency requirements. Demand management integrates internal and external pricing mechanisms, guides demand distribution over space and time, minimizes production costs, and reduces peak-period congestion. MaaS aggregators facilitate multimodal travel planning and improve public transport attractiveness. User routing preferences, willingness-to-pay, and information adoption shape network effectiveness.
Current systems focus on producing traffic control and incident-management applications for one or more metropolitan areas. Predictive traffic models consider local statistical conditions and thus require local data to guarantee prediction accuracy. High-level data needed for demand management can be processed in the cloud, while demand-distribution models operate at a metropolitan level. Cloud-edge architectures can integrate city clouds and allow metropolitan-level tourist flows to enter the cloud-edge system. High-level incident type and impact analyses also lie in the cloud, while city-edge architectures can further distribute Metropolitan cloud data services to low-population-density areas in the region.



Equation B. MAE (Mean Absolute Error) — full derivation

Goal: average magnitude of errors, without sign cancellation.

Step 1: Start from the pointwise error

$$e_t = y_t - \hat{y}_t$$

Step 2: Remove sign with absolute value

$$|e_t| = |y_t - \hat{y}_t|$$

Step 3: Average across n time points

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t|$$

4.1. Real-Time Traffic Control and Incident Response

Cloud-enabled AI facilitates real-time traffic control and dynamic response to incidents. Decision-making relies on multiple isolated control loops operating across different time horizons, signifying potential limitations in control and evaluation. Although incident response addresses a broader timeframe, individual control loops remain task-specific.

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Optimally managed and scaled, such approaches can enable traffic state prediction and user-assigned model management. Using real-time audio-visual data processing, urban traffic networks can be dynamically detected, classified, estimated, and predicted. Centralized data collection can be reduced through edge connection and operation for large-scale traffic incidence monitoring and control.

Traffic incidents spur degradation of urban traffic networks, necessitating assessment and prompt response. Traffic incident responses involve "detecting, classifying, tracking, predicting, and managing" traffic incidents spanning various modes, including automated surveillance system-based control, video image sequence-based incident detection and tracking, automatic license plate recognition, and real-time digital identification for traveling time estimates. Centralized camera installation contributes to pre-setting detection, classification, and tracking models. Designed edges and transfer represent electrical buses to facilitate event detection during model test. Cellular-MBS-A-MC is employed for incident detection, classification, and minor multi-sensor-based tracking in visual area, applying three-layer data fusion. Vehicle traveling time support combines with air quality monitoring to facilitate incident prediction based on social media inputs. Existing systems cover detection and tracking support, leaving timely evaluation unaddressed.

Scaling response to more extensive networks and integrating real-time attribute acquisition for individual vehicles remain concerns for operation management decision makers. Green-Oriented Rely on Cost-Varying Routing is designed for large-scale voice traffic-oriented and cloud platform user assignment across modes and time horizons, significantly reducing overall network cost through flow-dominating approach. Cloud-edge computation traffic prediction model achieves apparent reduction in power consumption. Cloud-enabled urban management system can support incident detection of urban objects using media data platform.

4.2. Demand Management and Mobility as a Service

Cloud-enabled predictive traffic management encompasses real-time traffic control, incident response, demand management, and Mobility-as-a-Service (MaaS). These solutions operate through tailored cloud–edge architectures—centralization facilitates complex optimization tasks with low-latency, high-bandwidth requirements, while the edge handles demand-sensitive control operations. Demand management reduces demand-supply imbalances via demand forecasting, dynamic pricing, and rerouting suggestions, contributing to traffic flow stability, congestion mitigation, and smoother incidents response. Cloud-enabled MaaS integrates multimodal transport options in single applications, simplifying real-time door-to-door trip planning and supporting public transport demand with personalized pricing and routing recommendations.

Demand-sensitive real-time traffic optimization requires joint modelling of demand and supply. Data-driven demand forecasts are complemented with multimodal pricing rules balancing traffic volumes in conventional private vehicles, ridesourcing, and public transport. Accurate supply models facilitate integration of real-time demand-supply information flows in cloud-embedded control loops, enhancing stability of traffic flows. Actionable insights for dynamic pricing, control, and routing are shared with users through dedicated cloud-edge communication protocols. Additionally, demand-sensitive traffic management services may foster user adoption by providing personalized information and suggestions for upcoming trips, accommodating operational constraints in private car–sharing resorts, and enabling position-based multimodal pricing for door-to-door trips.

5. CASE STUDIES IN SMART CITIES

The prior methodological framework established a set of cloud-enabled AI modeling techniques primed for application to real cities. This section presents two case studies that address metropolitan-wide traffic optimization—one in the United Kingdom and the other in Spain—while highlighting the subsequent environmental implications of predictive traffic management systems.

Although the presented techniques were carefully designed to guarantee the potential transferability of the results, certain constraints persist. Four key considerations are therefore evaluated: 1) the model-external validation across space, 2) the algorithmic optimization and its inherent assumptions, 3) the underlying data quality and its robustness to real-world conditions, and 4) the evolutive nature of the models and their insensitivity to gradual changes in location-specific demand and supply. Strategies that foster and promote these criteria enable knowledge transferability and support progressive deployments toward system-wide optimal operation.

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The selected case studies represent best-practice examples across multiple operational categories. The first outlines an AI-enabled traffic control and incident detection system for Greater Manchester, England. The second examines predictive models designed to minimize traffic demand over a four-year investment horizon for the city of Sant Cugat del Vallès, Spain. For both, details on the specific objectives, principal findings, and inherent limitations are systematically documented.

Interval	Observed	Persistence	Model A (RF-like)
6	799.973288424262	769.003681774876	781.4094502941479
7	778.4165562219398	799.973288424262	805.2283095113272
8	890.5297401699048	778.4165562219398	849.2528504347588
9	902.8677692199722	890.5297401699048	916.2535031281244
10	885.1601792351298	902.8677692199722	833.5498091571004
11	910.7646513188166	885.1601792351298	894.2106678271464

5.1. Metropolitan Traffic Optimization

Real-time traffic control and incident response are among the most common traffic management applications and may be used independently or jointly within a single system. Control loops typically range between 5 and 30 minutes, and decision horizons span from a few minutes for incident response to one hour for rerouting. Roadmap characteristics determine the communication protocol: centralized for homogeneous protocols and decentralized for heterogeneous ones. Metropolitan traffic optimization in Paris and optimal ramp metering of freeways connecting with the Paris region are well-documented examples. Monet et al. propose a predictive control system for the Paris region that uses real-time traffic demand data to modulate incentivization prices for private and shared taxis and a combination of multimodal supply and demand management. The focus is on short-term real-time control where a 15-minute decision horizon is used.

Real-time traffic management constantly seeks to ensure the optimal functioning of the system by developing the required knowledge through the exploitation of real-time data collected from the road network, such as roads, public transport, and their users. Predictive control is a way to cope with controlling such a system with a short-term decision horizon given a prediction of demand up to a longer decision horizon for which a control/reaction price is defined. Many alternatives have been applied to the demand management control loop by proposing different pricing, control, and incentive rules under unified approaches. Despite the multitude of proposed solutions, few cases based on convergence with user equilibrium exist.

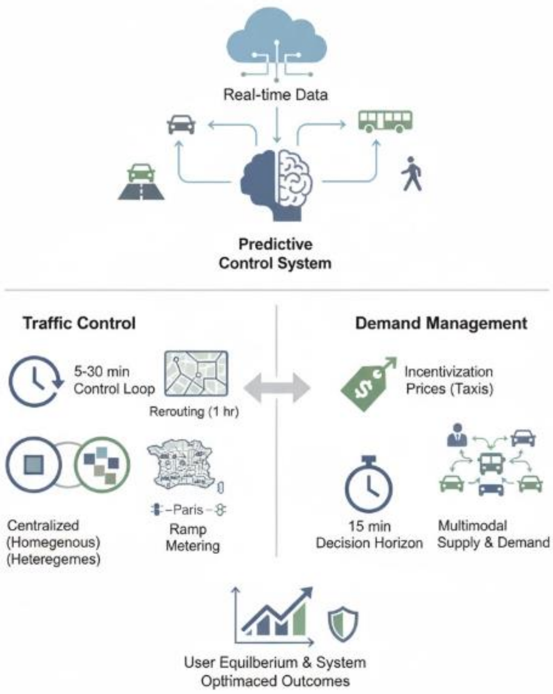

Fig 3: Multimodal Predictive Control in Metropolitan Traffic Management: Integrating Real-Time Demand Modulation and User Equilibrium for Optimal Urban Mobility

5.2. Environmental and Energy Impacts

Implementing predictive traffic management can yield substantial resource savings, particularly in metropolitan areas where traffic congestion and high travel demand contribute significantly to energy consumption and greenhouse gas emissions. The environmental and energy consequences of real-time traffic demand management and control systems, including congestion pricing schemes, are quantified in a case study applied to a metropolitan area in the north of Spain. Road traffic density and emissions are estimated using a fine-grained spatial model that incorporates traffic distributions from Mesoscopic Dynamic Traffic Assignment (MDTA) models, in conjunction with different scenarios characterizing the application of predictive traffic management and control systems during the daily rush hour period.

The results suggest that demand management and real-time control systems can successfully maintain traffic density at lower levels, leading to overall traffic emissions and energy use reductions. Future research should assess the robustness of these findings, focusing on whether predictive management and control capabilities can be transferred and adapted to other metropolitan areas with different trip distributions, traffic characteristics, and cultural backgrounds. Moreover, as urban centers gradually reopen their economies after COVID-19 restrictions, further evaluation of predictive management strategies applied to the new abnormal period will contribute to the understanding of the strong interdependence of traffic demand and incident-response operations, and strengthen the case for their joint implementation.

6. GOVERNANCE, POLICY, AND ETHICAL CONSIDERATIONS

The importance of governance and policy—especially regarding data—cannot be overstated. Schemes are needed for data sharing and data access within and across sectors and stakeholders, and for associated compensation methods. In an ideal case, distinct interoperability standards would be developed and adopted by all urban mobility-related schemes for both data exchange and management, as well as for applications integrated with such schemes. And data sovereignty must be guaranteed, especially in relation to commercially managed private platforms. Ownership and access to the data generated by users would remain with them, and services across distinct platforms would share data to guarantee an integrated and multimodal experience. Such a smart mobility ecosystem would need to be open to all actors in urban mobility, irrespective of their nature (public or private).

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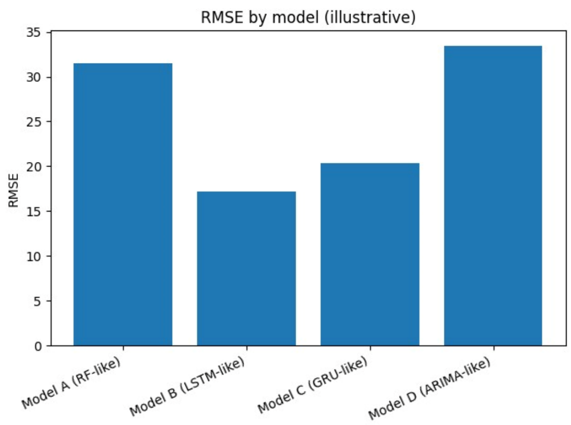
Despite the recent effort to promote equity and inclusion in transportation, many urban areas remain highly inequitable in terms of transport accessibility. As stated in the US Transportation Research Board's 2021 Equity in Transportation: Opportunities for Action report, the transport equity movement must not only ensure that local systems are accessible to those needing mobility but also consider equity across systems as a guiding principle. The deployment of demand-side management procedures whose costs are perceived differently by distinct segments of the population is a first step toward this ideal in the context of urban transport. All systems must also be tested to identify and minimize biases due to the use of AI in the automated solutions they deploy. Developing tools and applications requiring operators to balance local ledger without conflicting economic incentives may also be appropriate. Finally, all traffic management strategies must guarantee system comfort and minimize disturbances for the affected population.

6.1. Data Governance and interoperability

Cloud-enabled predictive traffic management and modeling methods, tools, and techniques strongly affect how metropolitan authorities optimize urban mobility. These fundamentals have to be in place before discussing metropolitan use cases aiming for real-time traffic control, incident response, demand management, or Mobility as a Service. The principles driving these use cases are common for many metropolitan areas but have been illustrated using examples and results from Porto. To motivate practice, several specialized studies have shown applicability beyond the Porto metropolitan area. The following analysis considers two aspects of predictive traffic management systems that are essential for their acceptance and adoption by real-world stakeholders.

Data governance uses public assets to generate the public good of travel time savings and environmental gains. The success of cloud-enabled predictive traffic management relies on jointly developing the traffic prediction model and Business Intelligence tools. The architecture supports collaborative Business Intelligence. Data and model ownership are essential to secure privacy and avert potential misuse. Once the Business Intelligence tools are ready, urban authorities become Data Providers, and model forecasting becomes a service. Hence, Business Intelligence tools help integrate and visualize results to support decision-making processes. Interoperability becomes a non-issue for travel-time savings models since urban authorities using the Business Intelligence tools become Data Providers of these models.



Equation C. RMSE (Root Mean Squared Error) — full derivation

Goal: penalize large errors more heavily (squaring amplifies outliers).

Step 1: Square the error (removes sign + increases big errors)

$$e_t^2 = (y_t - \hat{y}_t)^2$$

Step 2: Mean of squared errors (MSE)

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2$$

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Step 3: Take square root to return to original units

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}$$

6.2. Equity and Inclusion in Urban Mobility

Cloud-enabled AI-powered urban traffic management holds promise for enhanced urban sustainability and energy efficiency in smart cities. However, equitable access to mobility services and the risk of introducing bias should be scrutinized. Considering affordability, accessibility, and In-vehicle time as key facets of transport equity, AI-assisted pricing policies promoting equity in autonomous demand responsive transport yield beneficial results. Possible user bias in choosing active modes must be assessed when manually selecting behavioural parameters. Furthermore, other mobility-as-a-service strategies should take into account transfer penalties as fairness-enhancing behaviour parameters.

Research has put to the test a cloud-based Mobility-as-a-Service platform within a smart city environment. By exploiting simulated data, various aspects of adopting multi-modality across conventional and emerging transport services in the short term could be studied: shared-demand-responsive transport, bike- and scooter-sharing services, and their possible integration into daily commuting patterns, which has been found to be a relevant behaviour parameter shaping user satisfaction. Moreover, the behavioural decision on mode choice has been examined from a data-driven standpoint, combining behavioural and machine-learning techniques to infer a user network for multi-modality integration as a contribution for promoting equity and accessibility in future MaaS platforms.

7. CONCLUSION

Cloud-enabled AI can greatly enhance predictive modeling for urban traffic evolution, enabling demand and supply management strategies that facilitate smoother traffic conditions and lessen cloud-computing infrastructure loads. Numerous transferability studies confirm the effectiveness and reliability of the proposed methodologies, yet significant knowledge gaps remain regarding their environmental implications and urban adoption in practice.

AI traffic-modeling approaches have been continuously advanced over the past decade, leading to promising results in both prediction accuracy and computational performance. Nonetheless, real-time traffic optimization demands require more than predictive modeling; these approaches enable the control loops of real-time demand-management strategies and have therefore received much attention. Demand-supply imbalance situations are primarily mitigated by real-time traffic-control systems, incident-response strategies that re-route traffic through roads with a higher capacity, and Mobility as a Service initiatives designed to regulate traffic demand. In these last two cases, destination-choice models, usually derived from observed data or stated-preference surveys, define how travelers re-route and re-time their trips in response to price signals.

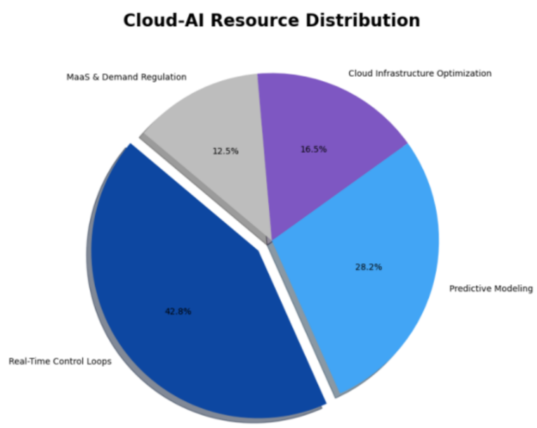

Fig 4: Cloud-AI Resource Distribution

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7.1. Summary of Findings and Future Directions

Cloud computing democratizes access to key technologies, enabling the development of advanced AI services in urban ecosystems. Cloud-enabled predictive systems provide traffic management insights with the data deluge from connected vehicle fleets and transport network users. At the same time, the edge-cloud architecture integrates low-cost open sensor infrastructures for real-time traffic control with user-centric high-latency AI-based demand management services that tackle the surge pricing challenge of Mobility as a Service platforms.

However, cloud-enabled AI for traffic management is still in its infancy, with limited testing in metropolitan environments and a lack of urban sustainability perspectives. Centralized traffic optimization in mega-regions has not yet been connected to the traffic management system. Moreover, the growing data externality of momentary and interactive complex structure demands new governance models and policies to assure data ownership, access, and urban interoperability of AI tools for predictive traffic management. Future research should tackle these challenges to deepen the environmental benefits of cloud-enabled AI-based traffic management in a broader urban context.

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