CITTA 14th Conference on Planning Research
Safe, Equitable and Just Communities

Data-driven and user-centric tools for a more resilient and inclusive public transport

Elisabete Arsenio[1], Rui Henriques[2]

1. Departamento de Transportes, LNEC, Lisboa, Portugal

2. INESC-ID and Instituto Superior Técnico, Universidade de Lisboa, Lisboa, Portugal

e-mail: earsenio@lnec.pt, rmch@tecnico.ulisboa.pt

(+351) 21 310 0300

Integrated public transport systems are essential for cities to respond effectively to citizen's accessibility needs and enable mobility of the most vulnerable population during disruptive events. The recent SARS-CoV2 pandemic revealed the importance of developing data-driven and user-centric tools for the dynamic monitoring of transport to reach sustainable mobility goals.
The research presented in this paper is built on the Integrative Learning from Urban Data and Situational Context for City Mobility Optimization (ILU) project, a national research and innovation effort funded by the Portuguese Foundation for Science and Technology, in cooperation with the city of Lisbon and main public transport operators. The ILU project managed to develop and validate new planning tools anchored in data science methods to dynamically support the context-aware description, prediction and optimization of urban mobility while detecting vulnerabilities in the public transport system that hinder social equity and resilience. This work introduces the developed computational system, iLU APP, which integrates pivotal algorithms enabling descriptive, predictive and prescriptive multimodal traffic analytics to support decision making. The following functionalities, amongst others, will be discussed: i) detection of spatiotemporal, emergent and multimodal urban traffic patterns from multiple urban data sources (integration of big data); ii) deep learning approaches in graphs and recurrent networks for context-sensitive urban traffic prediction; iii) efficient inference of origin-destination (OD) matrices, dynamic, multimodal and with detailed statistics addressing passenger-sensitive service quality indicators such as waiting and travel times, walking distances and number of transfers; and iv) differential OD analysis of vulnerabilities in public versus private transport.

Keywords: sustainable urban mobility; artificial intelligence; multimodal transport; resilience; social equity

1 Introduction

Over time, cities' perspectives on sustainable mobility evolved from tecno-centrism to socio-centrism with an increased focus on accessibility provision, social and equity aspects (Lanzini and Stocchetti, 2021). Recently, the SARS-CoV2 pandemic reinforced the importance of dealing with disruptive and unpredictable events, paying further attention to the integration of resilience principles in sustainable urban mobility planning. Resilience in the context of urban mobility is the capacity of a social-ecological system to cope with disturbance, implying the ability to respond or (re-)organise in ways that maintain the system's essential functions, identity, and structure, while also allowing for adaptation, learning and transformation (POLIS and Rupprecht Consult, 2021). Considering the ever-growing complexity of urban dynamics, the challenge of transforming mobility requires cities to co-create and mobilise actionable systemic solutions and tools for supporting the development of integrated transport systems centred on efficient, clean, and seamless public transport options which should be sensitive to citizen's accessibility needs and mobility profiles. To this end, data science, machine learning and transport related sciences, along with an effective integration of big data from heterogeneous sources in cities, can be understood as the required fuels to facilitate the mentioned transformation, enabling transitions towards more resilient and inclusive public transport.

In an effort to answer the above challenge, the research presented in this paper is built upon the contributions of the *Integrative Learning from Urban Data and Situational Context for City Mobility Optimization* (ILU) project (2019-2022), which included the development and validation of new data-driven tools to dynamically support the context-aware description, prediction and optimization of urban mobility while detecting vulnerabilities in the public transport system that hinder social equity and resilience. The functionalities integrated in the iLU APP, validated within the context of the Lisbon city and its main public transport operators, provide recommendations for multimodal mobility management recurring to state-of-the-art machine learning methods.

The remainder of this paper is organised as follows. Section 2 presents the related work regarding data-driven and user-centric tools in the context of urban mobility. Section 3 presents the iLU APP, focusing on major innovative functionalities: 1) efficient inference of dynamic and multimodal origin-destination (OD) matrices with trip and transfer status; 2) detection of spatiotemporal, emergent and multimodal urban traffic patterns from heterogeneous urban data sources; 3) graph and recurrent networks for context-sensitive urban traffic prediction; 4) context-aware urban mobility optimization; 5) route choice and alighting stop estimators; and 6) differential OD analysis of vulnerabilities in public versus private transport. Finally, section 5 concludes and outlines further research directions.

2 Related work

Considering the literature on data-driven tools in urban mobility, few studies propose computational applications for multimodal public transport planning. Most of the previous related work tackles popular traffic data analytic topics focused on traffic flow modelling and prediction (estimating passenger or vehicle demand throughout a transport network), exploring several machine learning methods with mixed performance results (Nguyen et al., 2018). An example in the public transport domain is the work by Liu and Chen (2017), which proposes deep learning principles to forecast passenger demand in Taipei considering historical passenger flow data and other explanatory variables (e.g., temporal and holiday factors). Wang and Zeng (2019) state-of-the-art on data-driven methodologies and applications in public transport big data covers topics such as bus arrival times prediction, commuting behaviour mining and performance evaluation of public transport, being these mostly addressed in the works of Ma and Cheng (2019). Despite the relevance of these previous works, none provides actionable software systems covering multimodal public transport and related inclusion or resilience goals. As noted by Bibri (2019), previous research on big data analytics barely explores the complex challenges related to sustainability issues.

Coleman et al. (2018) developed a data-driven approach with the aim of prioritising bus schedules in New York public transport, focusing on functional parameters (service capacity versus actual ridership; scheduled versus actual running times). Ma and Wang (2014) used automatic fare collection (AFC) from smart cards and automated vehicle location (AVL) data in Beijing to develop a data-driven platform (web-based) for advanced travel information and monitoring public transport quality of service using several performance measures and statistics (e.g., network-level speed, route-level travel time reliability, stop-level ridership, headway variance). The previously mentioned works infer OD matrices able to deal with incomplete boarding data in flat-fare buses where: i) passenger origin inference is obtained by applying Bayesian decision-tree algorithms and Markov-chain optimization; and ii) passenger destination inference is solved through several analytical methods that include spatiotemporal transfer activity, daily trip chain analysis and historical travel pattern integration.

Tran and Draeger (2021) combined principles from complex network theory and hierarchical clustering to locate and assess the sustainability and equity impacts of hub investments in a multimodal transport network of three cities along the Pacific Northwest America Cascadia corridor. Overall, the proposed framework uses available open data sources e.g., geospatial asset data and network statistics, for planning multimodal hubs. In their approach, the weighting for each hub scenario is based on a normalized capacity score that includes the counting in each cluster (node degree) of the total number of incoming and outgoing public transport links (subway train, tram, bus), car and bike share slots.

Classic software solutions for the deployment of Intelligent Transportation Systems (ITS) generally provide simulation facilities to assess urban mobility decisions. INSIGMA software (Chmiel et al., 2016) integrates sensor deployment, data acquisition, and processing facilities for privacy-preserving traffic monitoring. In their work, state-of-the-art tools are surveyed in accordance with their primary functionalities, including traveler information (route planning, road condition information), traffic management (transport planning, traffic control, infrastructure maintenance), emergency support functions, vehicle services (vision enhancement, collision avoidance, safety readiness, commercial tools), regular public transport, and electronic tolling. Complementary ITS tools have been deployed for the analysis of traffic congestion (Silva et al., 2004), road network management (Singh et al., 2019), and the simulation-based analysis of necessary traffic conditions to reach sustainability goals (Jifeng et al., 2008). Some works place the focus on the architectural principles for the integration of existing urban mobility tools. HARMONY is a platform able to integrate in an interoperable manner activity-based models, mobility service management, and traffic simulation tools for the end-to-end evaluation of mobility system dynamics (Yfantis et al., 2021).
Krcmar et al. (2016) assessed 59 digital mobility services available as smartphone applications or web services - including services for trip planning, ride/car sharing, navigation, smart logistics, location-based information, and parking -, identifying innovation trends and open challenges within the existing service systems.

Considering context-aware tools, Chavhan et al. (2021) deployed an ITS system able to share incident, traffic, and weather data to nearby vehicles and medical emergency services using dedicated short-range communication protocols, which further supports route recommendation. Similarly, ITSMEI system monitors vehicle traffic to inform drivers about events taking place on the roads in real time (Quessada et al., 2020).

Software tools have been developed for complementary ITS ends, including the distributed control of large-scale urban IoT systems (Wu et al., 2018) and their cloud deployment (Ashokkmuar et al. 2015), the integrative energy management of multimodal mobility by for instance integrating the power supply of metro-lines with surface plug-in electric vehicles (Falvo et al., 2011), the classification of vehicles for traffic monitoring and controlling from different camera sensors (Husain et al., 2020), the evaluation of security and quality-of-service design requirements in ITS (Javed et al., 2018), the incorporation active mobility and amenity analysis in urban design tools (Dogan et al., 2020), or the integration of inexpensive vehicle-to-vehicle messaging using off the shelf LEDs and photo diodes in real-world ITS for road safety (Siddiqi et al., 2016).

3 Multimodal-oriented public transport planning from Big Data: the iLU App facilities

Considering the research gaps presented in the previous section, the works developed in the ILU project addressed two major identified needs in the context. First, the need to acquire actionable and integrative data-driven stances on urban mobility able to model end-to-end multimodal traffic dynamics from heterogeneous urban data sources, e.g., sources collected from both stationary and mobile sensors throughout the city of Lisbon. Second, the need to incorporate relevant associative links between traffic and their intrinsic situational context to aid the description, prediction and optimization of urban transport. By addressing these challenges, multiple scientific contributions have been proposed since 2019:

- discovery of actionable multimodal mobility patterns from urban data sources, focusing on emerging dynamics in the city, and correlations between traffic and its situational context;
- context-sensitive diagnosis and prognosis of vulnerabilities in the public transport system (e.g., transfer needs, demand-capacity bottlenecks);
- deployment of intelligent traffic systems to place mobility recommendations, with a focus on context-aware optimizers of public transport networks and adaptive traffic light controllers.

The iLU APP is the recommendation system that integrates the computational contributions developed in the iLU project. The facilities provided by the iLU APP, aligned with the structure of the iLU project, are organized around five groups (Figure 1): consolidation, visualization, description, prediction, and optimization facilities. Each group of facilities provides data analytics grounded on heterogeneous urban traffic data (road sensors, mobile data, smart card data) and situational context (weather, public events, urban planning, interdictions), establishing actionable results to support urban mobility decisions by carriers, municipalities, and other stakeholders.

The iLU APP system was designed to further meet quality requirements (interoperability, modularity, reliability, usability, data integrity, accessibility, extensibility) and can be securely configured on a server, allowing continuous and secure access via the browser or, alternatively, programmatically using standard APIs.

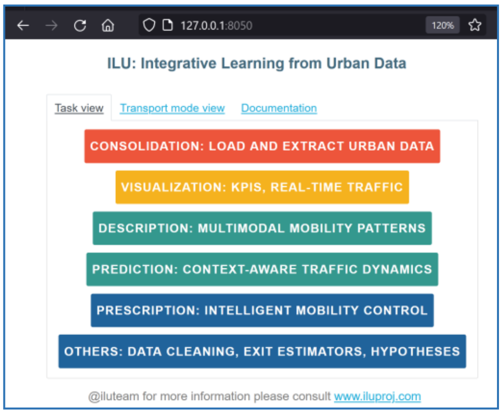

Figure 1. The iLU APP main menu

This section offers a guided in-depth view on how the developed analytical facilities contribute to more social equitable and resilient urban mobility ecosystems, through addressing main public transport network vulnerabilities. Section 3.1 lays the foundational facilities, centered on statistical and algorithmic principles for multimodal traffic data analysis, focusing on the dynamic inference of origin-destination matrices with trip and transfer status for assessing social equity goals. Section 3.2 addresses the need to respond to the ongoing changes in urban mobility, moving the focus from generative views of urban mobility to actionable pattern-centric views, exploring mechanisms to assess and strengthen the resilience of multimodal transport systems. Section 3.3, pushed by the need to incorporate sources of situational context to aid traffic data analysis, covers why context-aware analytics are essential to leverage sustainability drivers. Section 3.4, moves the focus from descriptive towards predictive ends with the aim of prognosing resilience and accessibility bottlenecks. In section 3.5, we show how previous descriptors and predictors can be used to develop data-grounded optimizers of urban mobility to reach sustainability goals. Finally, section 3.6 presents the role of preprocessing facilities and differential stances on private-public transport for leveraging resilience and social inclusion principles in public transport systems.

3.1 Multimodal mobility dynamics

Lemonde et al. (2021) provides foundational precursor work on the iLU APP. A multidimensional data repository with efficient spatiotemporal indexing mechanisms, as well as data updating and cleaning facilities, was developed to consolidate all available urban data sources with potential impact on city traffic analysis, including situational context data from external semi-structured repositories. In this work, spatiotemporal indices of multimodality are further explored to dynamically detect zones with the lack of adequate transport supply along specific time periods, as well as urban zones that, despite the presence of different transportation modes, are characterized by heightened imbalanced preferences towards specific modes of transport. Figure 2 provides an illustration of consolidated data access facilities and multimodality assessment maps in the iLU APP.

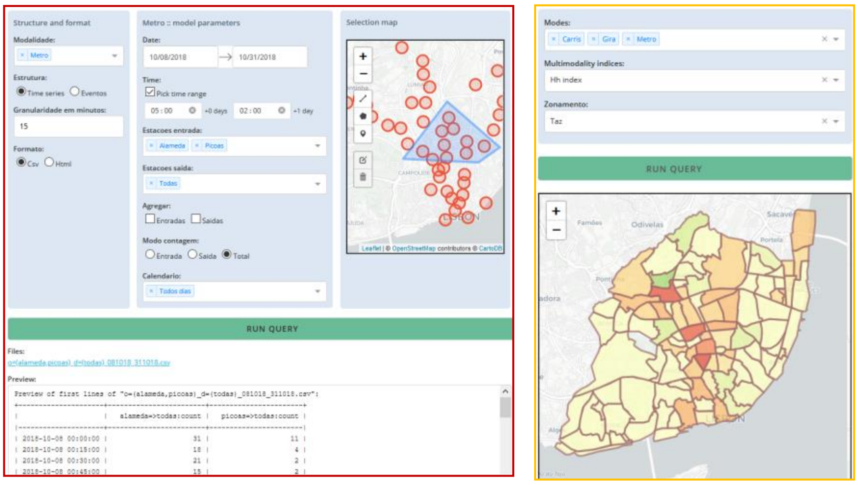

Figure 2. Consolidated urban data extraction facilities (*left*) and multimodality maps (*right*) in the iLU APP.

To understand mobility patterns in the city, as well as network vulnerabilities, the iLU APP extends classic views focused on the passenger flow to incorporate trip and transfer status (Cerqueira et al., 2021a). To this end, inference methods and visualization principles were developed to learn dynamic Origin-Destination (OD) matrices from multimodal smart card validations. More specifically, the proposed approach offers three major contributions: i) it efficiently computes several statistics that support OD analysis, helping with the detection of vulnerabilities throughout the transport network; ii) offers the possibility to decompose traffic flows in accordance with flexible calendrical rules, and user profiles; and iii) flexibly supports the selection of the multiple zoning criteria of varying spatial granularity. More specifically, statistics related to the range of passengers' functional mobility needs (commuters for working purposes, etc.), walking distances, transfer needs, and trip durations are supported by the inference methods. The visualization tool implements interactive spatiotemporal navigation facilities, providing relevant guarantees of usability. Figure 3 shows the presentation of the target dynamic OD matrices in iLU APP for the Lisbon city. Statistic-driven OD analysis in Lisbon revealed relevant spatial disparities on the quality of transport - mostly pertaining to waiting, transfer and walking needs -, with Santa Clara being one of the parishes with more vulnerabilities regarding connectivity and accessibility.

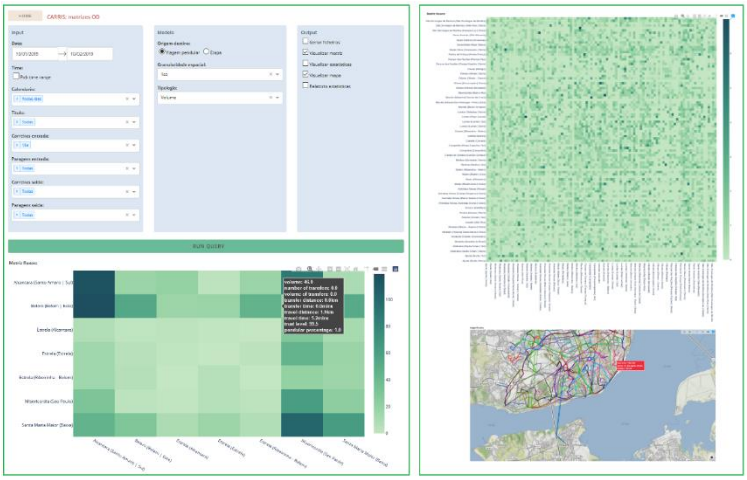

Figure 3. Dynamic origin-destination inference facilities in the iLU APP.

3.2 Handling emerging and disruptive traffic demand changes

A) *Discovery of actionable emerging patterns in road traffic*

Changes in urban mobility are pervasive, whether caused by shifting transport preferences, new traffic poles, or by disruptive events such as mobility reforms or pandemics. In this context, emerging patterns reveal ongoing changes in city traffic dynamics, whose growth may evolve to create traffic bottlenecks if timely precautions are not taken. Illustrative emerging traffic patterns include: transport routes with increasing demand at specific time periods; or road segments whose average speed, congestion extent, or throughput is increasingly hampered. The early detection of emerging patterns offers urban planners the opportunity to make the necessary provisions to urban mobility. The iLU APP implements a novel linear-time method proposed by Neves et al. (2020) to comprehensively detect emerging patterns within parameterizable spatiotemporal footprints from heterogoeneous traffic data, including smart card data or road traffic data. Statistical scoring is applied to ensure the actionability and relevance of emerging patterns.

Figure 4 shows congestion and decongestion traffic patterns from consolidated road traffic data from inductive loop detectors and WAZE's geolocalized speed data. Emerging pattern solutions are presented using both interactive tables and maps with spatiotemporal navigation facilities.

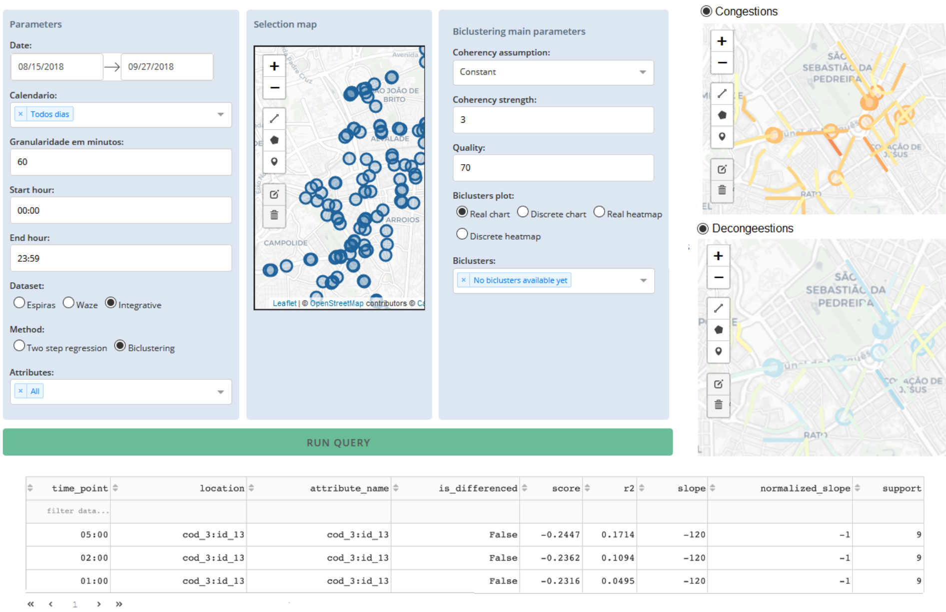

Figure 4. Emerging pattern discovery facilities in the iLU APP: road traffic (de)congestion cases.

The SARS-CoV2 pandemic reinforced the importance of developing data-driven and user-centric tools for the dynamic monitoring of transport. Hence, our research considered the impacts generated by this disruptive event in the Lisbon public transport (bus and metro). Aparicio et al. (2021) bridges statistical views, visualization principles, and temporal pattern mining advances to comprehensively explore changing urban mobility dynamics after a disruptive event (e.g., pandemic stage, mobility reform) from user trip data. Interactive maps (Figures 5 and 6) and order-disruptive traffic patterns are proposed to this end.

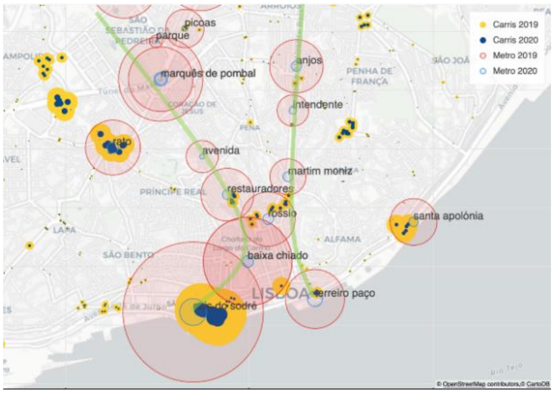

Figure 5. Pandemic-induced changes in transport demand (Aparicio et al., 2021a)

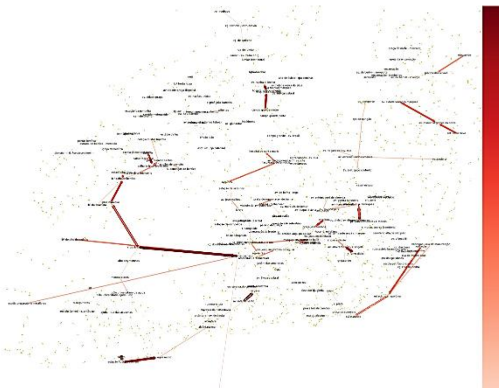

Figure 6. Demand-capacity resilience bottlenecks in the CARRIS bus-tram Lisbon's network (Aparicio et al., 2022)

B) *Modelling and assessing resilience in multimodal transportation systems*

Grounded on recent contributions by Aparicio et al. (2021b, 2022), the resilience of multimodal transport systems can be further assessed by the city/public transport operator through the iLU APP.

Resilience is seen in both static and dynamic settings, looking at aspects in the network topology and user flow and demand. In the static setting, stations and segments in the multimodal transport network can be selected to understand the impact of service disruptions (i.e., robustness) caused by malfunctions, shortage of resources or catastrophes. In the dynamic setting, passenger demand-transport supply (i.e., lean resilience) can be inquired from available smart card data and vehicle georeferencing. Figure 6 provides a view example of capacity-demand shortages along Lisbon's bus and tram networks.

3.3 Incorporating situational context to aid the learning facilities

Traffic dynamics are situated, dependent on a high multiplicity of situational context factors. The presence of large-scale events creates irregular peaks of demand; road traffic interdictions condition mobility; weather impacts transportation mode decisions, especially active modes of transport; changes to the city urban planning affect the way traffic is generated and attracted to different parts of the city throughout the day (Cerqueira et al., 2021b; Sardinha et al., 2021). Despite their well-recognized impact on urban mobility, principles for context-aware traffic data analysis remain largely dispersed and further fail to model the joint impact that these multiple sources of context exert on urban mobility. Leite et al. (2020), Cerqueira et al. (2021b) and Sardinha et al. (2021) establish principles for the automated acquisition of situational context data and their integration in traffic data analytics. Leite et al. (2020) place principles for the online consolidation and labelling of heterogeneous sources of context from public repositories, followed by the context-aware detection of traffic deviations against expectations. Figure 7 shows the iLU APP annotations on traffic series for the context-sensitive analysis of anomalous transport demand.

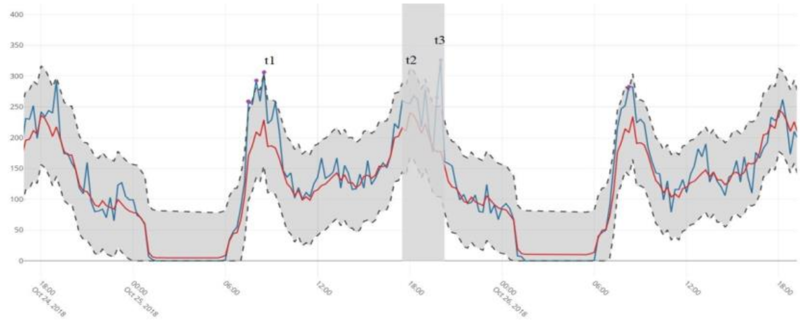

Figure 7: Available context data (vertical bars) and traffic deviations from expectations (dotted envelope) are both annotated over the observed/modeled traffic series in the iLU APP for a context-aware inquiry of anomalies and knowledge acquisition.

In Cerqueira et al. (2021b), context-aware learning principles were developed for different traffic data structures: i) georeferenced time series data; ii) origin-destination tensor data; iii) raw traffic event data. Considering Lisbon as a guiding study case, the gathered results quantify the impact that public events, weather factors or interdictions yield on OD pairs and traffic series.

3.4 From descriptive to predictive views: anticipating bottlenecks to urban mobility

Traffic flow prediction is considered a critical element for the successful deployment of intelligent traffic systems. The ILU project explored context-aware neural processing principles to address the inherent traffic variability, dependent on externalities such as weather and public events; and the absence of spatial awareness as the traffic at specific locations can be seen as a proxy to estimate traffic at nearby geographies. Dedicated forecasters were developed for road, bus-rail-tram and bike mobility (Figure 8).

Figure 8. Context-aware predictive facilities in iLU APP.

The work by Sardinha et al. (2021) proposes new neural processing principles to incorporate both historical and prospective sources of spatial, meteorological, situational and calendrical context in predictive models. To this end, a new recurrent neural network layering composed by serial long-short term memory (LSTM) components is proposed with two major contributions: i) the feeding of multivariate time series masks produced from historical context data at the input layer, and ii) the time-dependent regularization of the forecasted time series using prospective context data. Complementary to recurrent neural processing, graph and convolutional neural networks have been further explored with similar goals in mind. Rico et al. (2021) explored the role of graph structures to successful capture spatiotemporal traffic dependencies, as well as associations between heterogeneous data sources (e.g., loop counter and floating car data) and relationships between traffic and external factors (e.g., weather conditions and road accidents).

3.5 From predictive views into recommendations: optimising the urban mobility system

Multimodal end-to-end urban mobility flows along the day, such as those captured in dynamic ODs (section 3.1), untap the potential to develop public transport systems able to quickly adapt to the dynamic demand of the passengers. As part of the ILU research contributions, Silva et al. (2022) developed optimization procedures for efficient route set adaptation and scheduling using heuristic approaches. The proposed optimizers are provided as a standalone tool, interoperable with iLU APP to consume multimodal traffic flows processed from available traffic data sources. In particular, the implemented optimizers synergistically combine single- and multi-objective stances to better answer the transit network design and scheduling problems. Results in the Lisbon city show reductions in the pursued objectives, including average travel time and transfers per trip, up to 28.3%. Complementarily, adaptive traffic signal control (ATSC) solutions based on deep reinforcement learning (RL) advances were explored to alleviate mounting congestion. Varela et al. (2021) assessed how the different dimensions of the control problem affect the efficacy of ATSC solutions from micro-simulation scenarios grounded on monitored traffic data in the city of Lisbon. To address the challenge of RL-based systems to scale up, Coelho (2021) consider distributed learning paradigms where coordination and decentralized principles for decoupling vast transportation networks are explored. Similar to public transport planning optimizers, ATSC solutions are produced as a standalone tool, interoperable with the iLU APP.

3.6 Complementary facilities

A) *Alighting stop estimation and data quality enhancement*

The accurate estimation of the alighting of passengers in public transport (multimodal network) is essential to model traffic flows for the subsequent inference of origin-destination matrices and urban mobility optimization. iLU APP combines state-of-the-art principles for alighting estimation from smart card data, ranging from transfer and commuting travel movements towards pattern-centric behaviour, with applicability to multimodal transport networks. Results in the primary bus operator in Lisbon city, CARRIS, reveal that the correct combination of state-of-the-art principles and integration of different modes of transport can improve in 20pp the coverage of successfully estimated exits. As shown in Figure 9, alighting estimates can be produced using smart card data from a parameterizable period, and a robust confidence statistic is computed next to the imputed exit.

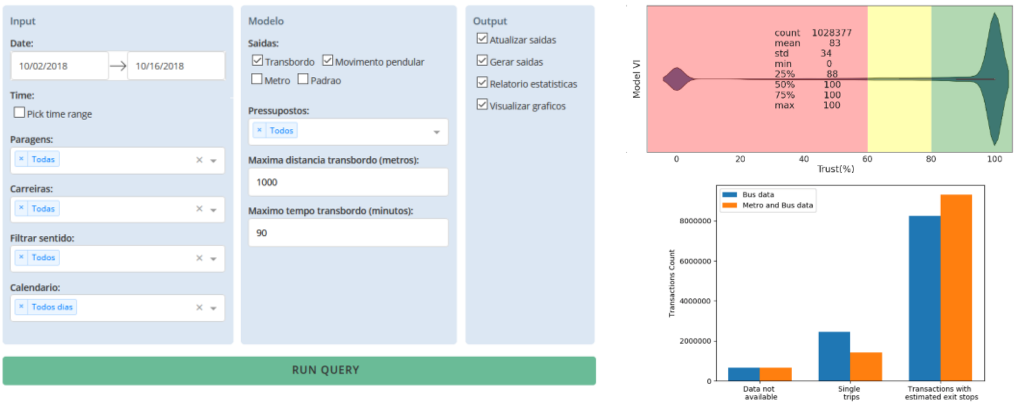

Figure 9. Alighting stop estimation in iLU APP: parameters and corresponding success levels.

Sensors deployed in urban traffic monitoring systems are not free of errors, e.g., inductive loop counters can become miscalibrated with time, transmission failures can occur in the acquisition of smart card transactions, geolocalized speed signals depend on the representativity of underlying mobile data. In this context, Sousa et al. (2021) proposed a computational system for the fully autonomous cleaning of (multivariate) time series data using strict quality criteria assessed against ground truth extracted from the targeted signal data. The proposed methodology, available in the iLU APP, is parameter-free as it relies on robust principles to assess, hyperparameterize and select state-of-the-art methods for time series imputation and outlier detection-and-treatment, considering both point and segment/serial errors.

B) *Route choice identification for enhanced resilience*

Another important need is to assess the position of passengers within multi-line rail transit systems. Understandably, passenger route choices are not deterministic as they depend on the subjective perception of travel time, required transfers, convenience factors, and on-site train arrivals and waiting times, among others. This makes it difficult to infer the volume of passengers along specific segments of the network at a given time. Tiam-Lee and Henriques (2021) propose a computational system, interoperable with the iLU APP, that identifies the individual passenger routes by aligning card validation timestamps against real-time route scheduling. In the absence of vehicle geolocation data, the locations of the trains at different times are estimated by analyzing passenger volume peaks at the exit station gates. The application of this computational system to Lisbon's metropolitan system revealed the presence of different groups of users placing different choices along the same entry-exit station pairs. Although the majority of preferred routes along the network corresponds to those with the least transfers, a considerable amount of choices is guided by shortest distance criteria at the expense of an additional transfer (Figure 11).

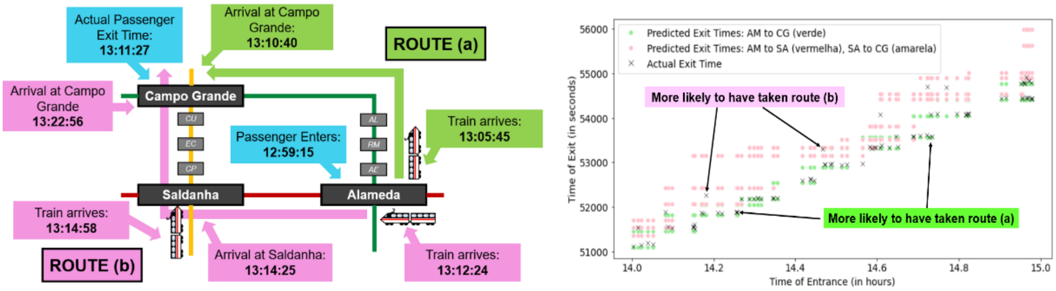

Figure 11. Route choice estimation facilities in the iLU APP (adapted from Tiam-Lee and Henriques, 2022).

C) *Differential private-public OD travel views for inclusive mobility*

Finally, to guarantee that public transport systems are sufficiently attractive against private options, the ILU project team further established analytical facilities to assess the comparative attractiveness of public transport against private transport per origin-destination pair. Departing from the state-of-the-art work (Cerqueira et al., 2021b) on dynamic and multimodal OD matrices with multivariate statistics, we have proposed an augmentation of these earlier OD matrices to comprehensively assess public versus private transport differences on both travel time and transfer needs. The inferred differential OD matrices, under deployment in the iLU APP, have been used to assess obstacles faced by specific user profiles and to make public transport options more attractive.

5 Concluding remarks

The computational outcomes of the ILU project, jointly developed with the major public transport stakeholders in Lisbon (bus, trams, metro, shared public bicycles), offer a first mark for the context-aware, data-driven, and user-centric optimization of urban mobility. Amongst other ends, the devised analytical facilities allow mobility planning decisions taken by the municipality and public transport operators to be fully transparent to the citizen (objectively derived from real data with strict statistical guarantees). Furthermore, the updatable, online and scalable nature of these facilities further ensure a continued alignment of the public transport network with the ongoing city transformations, ensuring that the public transport adapts to the emerging changes in traffic demand throughout the city, a growing need given the disruptions and changing regulations observed in pandemic contexts.

The iLU APP recommendation system is a pioneer in urban mobility, allowing a multimodal, dynamic and context-sensitive analysis of urban traffic, offering a means for objective and transparent coordination between operators, authorities and municipalities, capable of allowing a continuous alignment of the transport network with the current city dynamics.

By way of illustration, the identification of multimodal travel patterns from smart card data in the public transport network can unravel disparate levels of service regarding trip status and transfer needs, which can be used to establish reforms and policies oriented to sustainable mobility, paying attention to the public transport network and user vulnerabilities. Differential private-public transport trip views can guide the desired transitioning of traffic towards more sustainable and multimodal transport options, while addressing resilience principles. The comprehensive identification of these multimodal patterns further yields the potential to reveal rerouting and rescheduling needs (strategic planning) and, in the presence of planned large-scale events or unexpected occurrences, identify needs for temporary transport offer reinforcement (operational and tactical management), leveraging resilience needs in response to ongoing changes in the urban ecosystem.

Part of the computing facilities were already validated and are being used at CARRIS, the main bus and tram public operator in the city of Lisbon. Overall, we expect the novel contributions of the ILU project to nurture a continuous collaborative environment encompassing the whole urban mobility ecosystem, with multimodal transport and urban data management increasingly sensitive to the mobility needs of the citizen.

Acknowledgements

The authors thank Câmara Municipal de Lisboa, CARRIS and METRO for the provision of data and support. This research work was further supported by national funds through Fundação para a Ciência e a Tecnologia (FCT) under project ILU (DSAIPA/DS/0111/2018) and INESC-ID pluriannual (UIDB/50021/2020).

References

Aparicio, J., Arsenio, E., Henriques, R. 2021a. Understanding the impacts of the COVID-19 pandemic on public transportation travel patterns in the city of Lisbon. Sustainability 13.15, 8342; https://doi.org/10.3390/su13158342.

Aparicio, J., Arsenio, E., Henriques, R. 2021b, Assessing Robustness in Multimodal Transportation Systems: A case study in Lisbon, In European Transport Conference 2021 (ETC - on-line).

Aparicio, J., Arsenio, E., Santos, F.C., Henriques, R. 2022, LINES: muLtImodal traNsportation rEsilience analySis, Sustainability, 14(13), 7891; https://doi.org/10.3390/su14137891

Bibri, S. E. (2019). The anatomy of the data-driven smart sustainable city: instrumentation, datafication, computerization and related applications. Journal of Big Data,6(1), 1-43.

Bubicz, M., Arsenio, E., Henriques, R., Barateiro, J. 2022. Sustainable Urban Mobility Measures in Response to Covid-19 a Systematic Literature Review and Emerging Policy Challenges. DOI: https://dx.doi.org/10.2139/ssrn.4055178.

Cerqueira, S., Arsenio, E. & Henriques, R. 2021a. On how to incorporate public sources of situational context in descriptive and predictive models of traffic data. ETRR 13. DOI: https://doi.org/10.1186/s12544-021-00519-w .

Cerqueira, S., Arsenio, E., Henriques, R. 2021b. Inference of Dynamic Origin-Destination Matrices with Trip and Transfer Status from Individual Smart Card Data, In European Transport Conference (ETC - on-line).

Cerqueira, S., Arsenio, E., Henriques, R. 2022. Is there any best practice principles to estimate bus alighting passengers from incomplete smart card transactions? In TRA Lisbon, Portugal.

Chavhan, Suresh, et al. "An efficient context-Aware vehicle incidents route service management for intelligent transport system." IEEE Systems Journal 16.1 (2021): 487-498.

Chmiel, Wojciech, et al. "INSIGMA: an intelligent transportation system for urban mobility enhancement." Multimedia Tools and Applications 75.17 (2016): 10529-10560.

Coelho, M. 2021. Critical Review of Reinforcement Learning Based Adaptive Traffic Signal Control. Thesis, IST UL

Coleman, M., Tarte, L., Chau, S., Levine, B., & Reddy, A. (2018). A data-driven approach to prioritizing bus schedule revisions at New York City transit. Transportation Research Record, 2672(8), 86-95.

Dias, G., Arsenio, E., Ribeiro, P., 2021. The role of shared E-Scooter systems in urban sustainability and resilience during the Covid-19 mobility restrictions. Sustainability 13.13, 7084 DOI: https://doi.org/10.3390/su13137084.

Dogan, Timur, et al. "Urbano: A tool to promote active mobility modeling and amenity analysis in urban design." Technology| Architecture+ Design 4.1 (2020): 92-105.

Falvo, M., et al. "Energy management in metro-transit systems: An innovative proposal toward an integrated sustainable urban mobility system including plug-in electric vehicles." Electric Power Sys. Res. 81.12(2011): 2127-2138.

Husain, Agha Asim, Tanmoy Maity, and Ravindra Kumar Yadav. "Vehicle detection in intelligent transport system under a hazy environment: a survey." IET Image Processing 14.1 (2020): 1-10.

Javed, Muhammad Awais, et al. "Adaptive security for intelligent transport system applications." IEEE Intelligent Transportation Systems Magazine 10.2 (2018): 110-120.

Jifeng, W. A. N. G., L. U. Huapu, and P. E. N. G. Hu. "System dynamics model of urban transportation system and its application." Journal of Transportation Systems engineering and information technology 8.3 (2008): 83-89.

Krcmar, Helmut, Maximilian Schreieck, and Manuel Wiesche. "Modularization of Digital Services for Urban Transportation." 22nd Americas Conference on Information Systems, San Diego, 11.-14.08. 2016. 2016.

Lanzini, P., & Stocchetti, A. (2021). From techno-centrism to socio-centrism: The evolution of principles for urban sustainable mobility. International Journal of Sustainable Transportation,15(11), 815-825.

Leite, I., Finamore, A., Henriques, R. 2020. Context-sensitive modeling of public transport data, In Transport Research Arena 2020 (TRA 2020 Proceedings).

Lemonde, C., Arsenio, E., Henriques, R. 2021. Integrative Analysis of Multimodal Traffic Data: Addressing Open Challenges using Big Data Analytics in the City of Lisbon, European Transport Research Review (ETRR) 13.64, Springer Nature DOI: 10.1186/s12544-021-00520-3.

Liu, L., & Chen, R. C. (2017). A MRT daily passenger flow prediction model with different combinations of influential factors. In 2017 31st IC on Advanced Information Networking and Applications Workshops (pp. 601-605). IEEE.

Ma, X., & Chen, X. (2019). Public transportation big data mining and analysis. In Data-Driven Solutions to Transportation Problems (pp. 175-200). Elsevier.

Ma, X., & Wang, Y. (2014). Development of a data-driven platform for transit performance measures using smart card and GPS data. Journal of Transportation Engineering,140(12), 04014063.

Neves, F., Finamore, A., Henriques, R. 2020. Efficient discovery of emerging patterns in heterogeneous spatiotemporal data from mobile sensors, In EAI MobiQuitous. DOI: 10.1145/3448891.3448949.

Neves, F., Finamore, A., Madeira, S., Henriques, R. 2021. Mining actionable patterns of road mobility from heterogeneous traffic data using biclustering, In IEEE Trans. on Intelligent Transportation Systems. 10.1109/TITS.2021.3057240.

Nguyen, H., Kieu, L. M., Wen, T., & Cai, C. (2018). Deep learning methods in transportation domain: a review. IET Intelligent Transport Systems, 12(9), 998-1004.

Nigro, M., Ferrara, M., De Vincentis, R., Liberto, C., & Valenti, G. (2021). Data Driven Approaches for Sustainable Development of E-Mobility in Urban Areas. Energies, 14(13), 3949.

POLIS, and Rupprecht Consult - Forschung & Beratung GmbH (eds). 2021. Topic Guide: Planning for more resilient and robust urban mobility

Quessada, Matheus S., et al. "ITSMEI: An intelligent transport system for monitoring traffic and event information." International Journal of Distributed Sensor Networks 16.10 (2020): 1550147720963751.

Rico, J., Barateiro, J., Oliveira, A. 2021. Graph Neural Networks for Traffic Forecasting, arXiv preprint DOI: https://doi.org/10.48550/arXiv.2104.13096.

Sardinha, C., Finamore, A., Henriques, R. 2021. Context-aware demand prediction in bike sharing systems: incorporating spatial, meteorological and calendrical context, arXiv preprint DOI: https://doi.org/10.48550/arXiv.2105.01125.

Siddiqi, K., A. D. Raza, and S. Sheikh Muhammad. "Visible light communication for V2V intelligent transport system." 2016 IC on Broadband Communications for Next Generation Networks and Multimedia App. (CoBCom). IEEE, 2016.

Silva, L., Manquinho, V., Henriques, R. 2021. UNIANO: robust and efficient anomaly consensus in time series sensitive to cross-correlated anomaly profiles, In SIAM International Conference on Data Mining (SDM).

Silva, Bruno Castro da, et al. "ITSUMO: an intelligent transportation system for urban mobility." International workshop on innovative internet community systems. Springer, Berlin, Heidelberg, 2004.

Silva, V., Finamore, A., Henriques, R. 2022. On the Role of Multi-Objective Optimization to the Transit Network Design Problem, arXiv preprint DOI: https://doi.org/10.48550/arXiv.2201.11616.

Singh, S., Ankit Saraswat, and Surendra Yadav. "Traffic simulation integration using SUMO simulator." International Journal of Scientific Research and Review 7.2 (2019): 22-26.

Sousa, R., Amado, C., Henriques., R. 2021. AutoMTS: Fully Autonomous Processing of Multivariate Time Series Data from Heterogeneous Sensor Networks. In EAI QShine, pp. 154-178, Springer

Tiam-Lee, T., Henriques, R. 2021. Where are the Passengers? Individual Passenger Route Choice Estimation from Gate Information in Urban Rail Transit Systems, In European Transport Conference (ETC – on-line).

Tran, M., & Draeger, C. (2021). A data-driven complex network approach for planning sustainable and inclusive urban mobility hubs and services. Environment and Planning B: Urban Analytics and City Science, 48(9), 2726-2742.

Varela, G., Santos, P., Sardinha, A., Melo, F. 2021. A Methodology for the Development of RL-Based Adaptive Traffic Signal Controllers, AAAI Workshop on AI for Urban Mobility (AI4UM).

Wang, Y., & Zeng, Z. (2018). Data-Driven solutions to transportation problems. Elsevier.

Wu, Di, et al. "Towards distributed SDN: Mobility management and flow scheduling in software defined urban IoT." IEEE Transactions on Parallel and Distributed Systems 31.6 (2018): 1400-1418.

Yfantis, Lampros, et al. "A Software-Agnostic Agent-based Platform for Modelling Emerging Mobility Systems." 2021 7th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS). IEEE, 2021.