The contribution of Machine Learning for Optimized Management :Urban Networks in Smart Cities

مساهمة التعلم الآلي في الإدارة المُحسَّنة: الشبكات الحضرية في المدن الذكية

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Abstract:

This article explains how machine learning algorithms transform smart cities by optimizing operational efficiency through network management. Therefore, by processing more abundant data, the ML algorithms perfect their ability to identify atypical behaviors, adjust dynamic flows and reduce energy consumption. Their implementation raises challenges, so it is crucial to evaluate their promises and challenges to judge their relevance to the future requirements of the city.

Keyword: Machine learning; urban networks; smart cities; infrastructure optimization; urban sustainability.
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1. Introduction :

The rapid urbanization of the XXI century poses unusual problems to the mechanisms of urban infrastructure (Shahidehpour, Li, & Ganji, 2018). The increasing densification of urban spaces has put unprecedented pressures on transport, energy, water and telecommunications systems.

This increased complexity of urban systems and the environmental requirements in terms of sustainability and operational efficiency make conventional approaches unsuitable for their management (Abujder Ochoa, Iarozinski Neto, Vitorio Junior, Calabokis, & Ballesteros-Ballesteros, 2025).

Moreover, large volumes of data can be analyzed by artificial intelligence algorithms, in particular machine learning, in order to identify trends and anticipate failures (Muhammad, Aseere, Chiroma, Shah, Gital, & Hashem, 2021).

But the application of AI in urban environments raises the following question: is it possible to optimize these infrastructures in a reliable, economic and ecological way? This question is at the heart of the current challenges of smart cities, because technological concepts are often out of step with reality.

Our study critically analyzes the conditions for a successful integration of machine learning in urban management, while identifying both the potential advantages and disadvantages.

2. Main machine learning techniques used :

The optimization of urban networks is based on the integration of ML methods. These methods focus on the challenges and problems posed by smart infrastructures. Also, a multitude of methods is proposed which varies according to the available data, the objective of the method (prediction, classification, optimization, etc.) and the complexity of the system studied (Yan, Jiang, Huang, Zhang, & Zhou, 2023).

Each of them contributes to finding a solution to a specific problem. Here are some examples applicable in this context:

2.1.Supervised learning :

Supervised learning is undoubtedly the most commonly used technique in the urban context. It consists in training a model on a set of

labeled data, that is to say whose results are known in advance, in order to allow the prediction of values for new observations. These techniques can be applied, for example, to metropolitan networks for:

- Predict energy or water consumption based on contextual data (temperature, special events) and temporal data (seasons, periods) (Miled, 2022)
- Calculate occupancy rates or transport flows in specific urban areas (Bin Hariz, Said, & Mouftah, 2021).
- Exploit the history of technical anomalies to predict problems or disturbances perturbations (Zhang, Li, Yu, Li, Hui, & Zheng, 2020).

As examples of methods, random forests are used for their robustness against noisy data, logistic or linear regression, and support vector machines (SVM) for the classification of complex scenarios.

2.2.Unsupervised learning :

On the other hand, unsupervised learning explores unlabelled data and highlights hidden structures or unexpected regularities. In urban environments, its usefulness is very valuable for:

- Segment user profiles (for example, in public transport or energy consumption) in order to adapt to the services offered (Mutule & al., 2021).
- Detect anomalies or unusual behaviors (for example, water leaks, overcharging or fraud). Clustering (most often K-means or DBSCAN algorithms) and principal component analysis (PCA) are probably the most used methods. The PCA makes it possible to reduce the size of the data while preserving their essential characteristics.

2.3.Reinforcement learning :

Inspired by behavioral learning mechanisms, reinforcement learning allows a software agent to interact with a dynamic environment and learn to optimize its decisions based on the feedback it receives (rewards or penalties). This type of model can be extremely useful in demanding real-time adaptation cases, such as:

- Adaptive traffic light control to improve traffic flow (Cappi, Monti, & Tosi, 2022).
- The regulation of energy consumption in smart grids;

- The reduction of the allocation of resources in case of overload or incident. Learning techniques such as Q-learning, Deep Q-Network (DQN) and actor-critic models can also find application in these scenarios.

2.4.Deep learning :

This learning strategy is based on multilayer artificial neural networks. When processing large and complex data sets, it offers exceptional performance, especially when these sets have significant geographical and / or temporal dimensions. It can be used concretely for:

- The processing of multivariate time series, such as urban sensor readings scattered around the city (Thai & Nguyen, 2020).
- The analysis of urban images captured by cameras or drones (for example, flow detection, object recognition, public space surveillance) (Kujawski & Dudek, 2021)
- High-resolution modeling of urban behavior (for example, modeling of environments with high spatial resolution).

3. Case study of the use of ML in smart cities :

Three examples from various socio-economic and geographical contexts have been selected to illustrate how ML can be used to optimize urban networks in a concrete and practical way:

3.1.Case Study 1 - Nairobi (Kenya): Transport Optimization (Williams, White, Waiganjo, Orwa, & Klopp, 2015)

Nairobi has launched the Digital Matatus project to improve transport in response to the growth of urban traffic. American universities have teamed up with the Kenyan government and the Health Commission to establish the mapping databases of collective minibus routes (matatus). From unsupervised clustering models and time series analyses, mobility patterns, saturation points and network anomalies are identified. The results allow a better planning of informal transport lines, priority areas for infrastructure improvement, and the provision of open data for locally adapted navigation applications. This case makes it possible to understand the impact of machine learning in contexts with low resources, provided that structured data is collected and shared.

3.2. Case Study 2 - Hangzhou (China) - Adaptive traffic Regulation (Ziang & Jihaeng, 2021)

Thanks to a partnership with Alibaba, the city of Hangzhou has been using artificial intelligence to ensure, in real time, urban traffic control since 2016 via the City Brain. The latter is based on reinforcement learning, which is based on data collected by cameras, sensors, GPS, or even traffic lights in order to allow dynamic adjustment of the duration of the lights, to optimize the routes of emergency vehicles and to predict possible traffic jams. The results have been impressive: a 15% reduction in traffic jams, fewer accidents and improved traffic flow. This project highlights the effectiveness of real-time adaptive approaches, requiring a dense and interoperable digital infrastructure.

3.3. Case Study 3 - Helsinki (Finland): Mobility Management (Hussain, Ahonen, & Leviäkangas, 2025)

With a view to predicting traffic patterns and optimizing multimodal transport services (buses, trams, bicycles, micro-mobility, etc.), Mobility Lab Helsinki aims to build and test smart and sustainable urban mobility solutions. It feeds GPS data, urban sensors and travel history, predictive models (supervised learning, neural networks, clustering).

At the heart of the solution are IoT sensors, data platforms and a digital twin of the city. If it is still in its experimental phase, it has already improved the city's traffic management and introduced new last-generation services, such as mobility in the sense of mobility as a service and produce concrete measurable effects: a potential improvement of 28% in CO2 emissions, a reduction in road congestion by 37% and an increase in public transport attendance from 15 to 23% due to shared first/last-mile services, thus testifying to the need for real-world tests, methods of adaptation by AI and public- private partnership, in order to ensure the success of smart cities.

The following table establishes a comparison between the three urban contexts mentioned above that use AI in their urban modernization approach.

Table 1: Use of Machine Learning in three urban contexts

Criteria	Nairobi (Kenya) **Optimization of transport**	Hangzhou (China) **Traffic regulation**	Helsinki (Finland) **Mobility management**
Main issue	Mapping and structuring a largely undocumented informal transport network.	To streamline urban traffic and reduce congestion in real time.	Develop, test and deploy smart and sustainable mobility solutions to improve transport services.
Type of urban network targeted	Mobility (network of minibuses "matatus").	Road mobility (urban traffic).	Multimodal transport networks: pedestrians, buses, trams, bicycles, shared cars, taxis, micro- mobility (scooters, scooters).
Mobilized ML techniques	Unsupervised learning (clustering, time series).	Reinforcement Learning and Deep Learning.	• Supervised learning for traffic and flow prediction • Clustering for user profiles. • Neural networks for predictive models.
Exploited data	GPS routes, observed schedules, passenger flows.	Video surveillance, road sensors, GPS data, traffic lights.	• Urban sensor data (traffic, environment) • Real-time data from transport operators. • GPS vehicle data. • History of user trips.

Results obtained	Better readability of the network, support for urban planning, public access to data.	Measurable reduction of congestion (~15%), optimization of emergency interventions.	• Potential reduction of CO_2 emissions by 28 %, • Decrease in road congestion by 37% compared to individual motorized trips, • Increase in public transport attendance from 15 to 23% thanks to shared first/last mile services.
Necessary infrastructure	Manual and collaborative GPS data collection (participatory project).	• Advanced digital infrastructure • Network of interconnected sensors.	• Digital twin of the city • IoT sensor network • Data integration platforms • Test applications for users.
Level of technological maturity	Emergent -simple solutions adapted to the context.	Very advanced - large-scale deployment in a smart city.	Intermediate to advanced – Current project (2022-2024), but already operational for experimentation in real environment.

Key lessons	The accessibility of data is a central lever for improvement in southern cities.	AI allows effective adaptive regulation when the infrastructure is mature.	• Experimentation in real conditions is essential for urban innovation • The ML allows a dynamic adaptation to mobility needs • Public-private collaboration key to success.

Source: table made by authors

4. Comparative analysis of the cases studied and key lessons learned :

The presentation of the three previous cases reveals a plurality of approaches mobilizing Machine Learning for the study of urban networks which is distinguished as much by contextual specificities and common dynamics. Even if the cases come from different regions and levels of development, they help us to better understand the conditions for activating AI tools in the contemporary city.

In this context, it is important to note that smart city projects are financed by several means, which may vary depending on the local context and the specific objectives of the projects.

This financing can come from various sources, such as: public financing, grants and aids, international financing, public-private partnerships, investment funds, private investments, as well as crowd funding (platforms allowing citizens to contribute directly to the financing of projects that interest them). However, in order to ensure the effectiveness of these approaches, it is essential to have a structured ecosystem for data.

This implies that information must be collected, examined and disseminated in a coherent way between all stakeholders, whether public or private in nature. It is also essential to have good governance, as it ensures that decisions are made in a transparent and participatory way, taking into account the requirements of citizens.Therefore, having a precise vision of the objectives to be achieved is essential to direct the efforts and gather the required resources.

4.1.Adaptability of machine Learning to local contexts :

One of the most interesting lessons is the enormous flexibility of ML techniques which can "work" in very different environments, just as much "with low technological infrastructure" (Nairobi) as very digitized (Hangzhou) or intermediate (Amsterdam). The Nairobi project demonstrates that fairly conventional unsupervised methods can be relevant if there is sufficient collection of correct data.

On the other hand, the "City Brain" system in Hangzhou, which exists thanks to a particularly dense digital environment integrating massive multimodal data in real time, mobilizes complex models such as Deep Learning.

Helsinki, for its part, is a prototype of the combination of innovative approaches combining advanced predictive techniques and ambitious urban policies, oriented towards innovation and towards a sustainable model of mobility systems.

4.2.The central role of data as a raw material for urban optimization :

In all the cases observed, the quality, availability and structuring of the data appear as sine qua non conditions for the success of the projects (Saujot & Erard, 2015). In Nairobi, the pooling of previously non- existent data has been a powerful lever for improving services. At the moment in Hangzhou, the sensors are working at full capacity and the systems interact so easily that they practically ensure instantaneous regulation of road traffic. In Helsinki, data makes it possible to model the city in real time, anticipate needs and guide mobility decisions. These examples demonstrate how the data ecosystem in which machine learning is used greatly influences its usefulness. Large data sets can be used to predict needs, improve procedures, identify problems and adapt to local conditions, thus creating value (Kujawski & Dudek, 2021).

4.3.Shared goals: performance, sustainability, quality of life :

Despite the extremely varied context issues (irregular/ informal mobility, congestion, transition to transport modes, energy transition), the three projects pursue the same goal of improving the efficiency of networks within the framework of social and environmental objectives, reflecting a general trend to integrate AI technologies not as an end in

itself, but as a means at the service of a more resilient, sustainable and inclusive urban governance.

But it is also a question of converging the notion of a smart city centered on users and users so that the algorithm helps optimize the reallocation of resources and reduce negative effects (pollution, waste, unequal access).

4.4.Common limits and challenges to overcome

Despite the benefits gained, many transversal challenges appear. First of all, the question of data governance, the updating of software, the computerization of interfaces, their anonymization, their accessibility ... are all subjects with technical, legal and ethical issues, as are the social acceptability of automated decisions, whether they are algorithms associated with traffic lights or energy management, while it is necessary to guarantee the transparency of algorithms and the decision system or maintain human control.

Finally, the transferability of the models from one city or territory to another is limited, because a successful system for one city may not be adapted to another territory due to the absence of infrastructure, data, and insufficient local impact.

These three case studies show that machine learning, far from being the prerogative of a few “high-tech” metropolises, can be applied in a differentiated way to plural urban problems.

Indeed, each city, even if it differs in terms of culture, level of economic growth andspecific needs, has managed to exploit technological advances to raise the standard of living of its residents.

In Nairobi, the integration of digital solutions was carried out to simplify access to public services. Mobile applications have been set up to allow residents to report infrastructure or health problems. In Hangzhou, an intelligent traffic management system has been introduced to improve traffic flow and reduce congestion. This device is based on the use of sensors and live data analysis.Finally, Helsinki has adopted a sustainability-centric approach, integrating green technologies into its urban policies to create more environmentally friendly living spaces.

However, for these initiatives to be effective, it is crucial to have a structured data ecosystem. It is therefore a question of collecting data, analyzing them and sharing them in a coherent way between the different actors, whether public or private.

Proper governance is also essential, as it ensures that decisions are made in a transparent and inclusive way, taking into account the needs of citizens. Finally, a clear vision of the objectives to be achieved is fundamental to guide efforts and mobilize the necessary resources.

However, its effectiveness does not depend so much on the sophistication of the algorithms but rather on the quality of the rooting of the project in the territory, the quality of the data and even more on the co-construction with the local actors of the implementation of the project.

Basically, it is the balancing of technology with context and meaning that makes the whole point of the potential of machine learning at the service of the sustainable city. Beyond simple technology, machine learning is becoming an essential way to strengthen the sustainability, inclusion and governance of these smart cities (Fang & al., 2023).

5. Conclusion :

By optimizing the management of infrastructures, essential to urban life, artificial intelligence, and more particularly machine learning, is on the verge of transforming urban systems.

The examples analyzed, in Nairobi, Hangzhou and Helsinki, show that these technologies are not reserved for the most advanced metropolises, but can be mobilized in very diverse contexts, provided we have a structured data ecosystem, appropriate governance and a clear vision of the objectives to be achieved.

Machine learning offers potential thanks to transparent algorithms, rigorous data processing and the widespread use of automated systems. The goal is to integrate AI in a way that facilitates and improves policies, rather than suppressing human decisions.

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