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DYNAMIC TRAFFIC LANES STRATEGY MANAGEMENT IN SMART CITY

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Abstract: Integrated domains, urban mobility, information and communication technologies (ICT), advanced parking solutions, and the shared economy drive the evolution of smart city ecosystems. This paper explores the strategic management of digitized urban street lanes as a transformative tool to improve traffic efficiency and overall city security. Traditional lane configurations are typically static, denoted as (n+n), where (n) lanes are permanently assigned to each direction. This assumes symmetric traffic distribution, which fails for real-time directional imbalances. Our approach defines two dynamic directional lane vectors {A}and {B} representing the active lane allocations, with (i+j=2n), the total number of available lanes. This allows real-time reallocation based on sensed traffic asymmetry. Our methodology transcends mere technological deployment, targeting infrastructure redesign for improved adaptability, security, and resilience. The proposed model enables streets to respond fluidly to dynamic demand, mitigating congestion, reducing fuel consumption and emissions, and reclaiming valuable urban time otherwise lost in traffic. A real-life case study illustrates the methodology's feasibility. We further validate our concept using a modified Nagel–Schreckenberg cellular automaton simulation enriched with game theory principles. This methodology provides a scalable path toward safer, more sustainable, and strategically managed urban infrastructure.

Keywords: Smart City, Floating Car Data, Cell Automata, Strategy Management, Security Systems.

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1. INTRODUCTION

Considering the smart city ecosystem, several key domains are foundational: urban mobility, information and communication technologies (ICT), advanced parking solutions, strategic security management, and the shared economy. These domains jointly accelerate the transformation of cities toward higher intelligence, efficiency, and resilience.

Conventional infrastructure relies on static traffic lane configurations as commonly symmetric, denoted as $n + n$ street lanes permanently allocated to each direction, irrespective of fluctuating traffic demand. This configurations usually lead to significant congestion and high inefficiency in peak hours.

In contrast, we propose a dynamic model for lane reallocation, guided by sensor inputs, FCD inputs and simulation models.

We define real-time lane allocation as directional vectors:

$$\text{vec}\{A\} = [a_1, a_2, \dots, a_i], \ \text{vec}\{B\} = [b_1, b_2, \dots, b_j], \text{ with } i + j = 2n \tag{1}$$

Here, vec{A} and vec{B} represent the current lane assignments for each traffic direction, while a_k, b_k represent operational states or capacity metrics of each lane segment. This representation enables responsive urban traffic optimization, enhancing throughput and safety in dynamically congested areas.

Our approach is not solely techno-centric but includes the redesign and strategic management of infrastructure in support of urban intelligence and security systems (Runyoro & Ko, 2013).

While techno-centric methods dominate smart city literature, they often conflict with sustainability goals when implemented without contextual constraints. (Munhoz et al., 2020)

A wide body of research addresses intelligent mobility through high-investment projects: solar-powered roads, piezoelectric surfaces, inductive charging lanes, musical and weigh-in-motion roads, and smart intersections utilizing V2X and VANET technologies. (Umedu, 2010; Atici et al., 2011; Toh, 2020).

However, the real-world scalability of these technologies often remains limited.

Despite multiple approaches to intelligent urban mobility, there is no universal consensus on optimal methodology.

Many proposed systems rely on brute-force deployment of technology without integration into shared economy models or behavioral infrastructure adaptation.

End user interaction is often minimal, with limited open data usage and negligible adaptability to existing infrastructure norms.

Shared economy concepts such as ride-sharing, vehicle pooling, high-occupancy vehicle lanes (HOV), and floating parking units (FPU) (Vujic, 2014) are essential but underdeveloped in major smart city deployments.

For example, bicycle sharing, scooter fleets, and car-sharing models have proven beneficial but remain marginal in terms of systemic integration.

Alternative transportation and sustainable transit methods - like Hyperloop systems (Cohn, 2021) - offer promise but require complementing structural reforms in urban layouts. Technological innovation continues to drive discussions about mobility intelligence (Soriano et al., 2018), but smarter traffic flow requires more than innovation: it requires predictive responsiveness.

Integrating smart infrastructure with responsive building and street networks can vastly improve both urban and rural ecosystems. Selective lane restrictions based on traffic types or schedules, when managed dynamically, can encourage non-traditional transit adoption and help reduce private car dependency.

Redefining transport infrastructure involves not only technological advancement but also the optimization of existing assets through dynamic reconfiguration. As mobility becomes more intelligent, it increases its capacity to integrate simulations results, sensor data, and socioeconomic modeling systems.

Empirical efforts, such as sociology-technical test-beds for smart urban mobility (Fryszman et al., 2019), illustrate the potential of simulation-based design and participatory governance.

This paper builds on those findings by developing its own simulation framework using Python (Lutz, 2013), C++ (Stroustrup, 2000), and Monte Carlo techniques (Rubinstein & Kroese, 2008) to analyze lane digitization scenarios.

Our proposed methodology, grounded in theory and tested through simulation, demonstrates how cities can apply vector-based lane optimization to improve real-time flow, reduce emissions, and enhance strategic security responsiveness.

2. LITERATURE REVIEW

In the context of techno-centric smart city development, this paper highlights selected key approaches relevant to mobility and infrastructure management. A comprehensive review is beyond this paper’s scope; however, the following notable models serve as foundational references for advancing smart mobility and lane management systems.

Multi-modal Integration: This approach emphasizes the unification of different transport modes - private vehicles, metro, buses, and shared mobility services - into a cohesive system for optimized movement of people and goods (Bagloee, 2019). While multi-modal systems significantly improve transport intelligence and urban sustainability, they typically require large-scale infrastructure investments and policy coordination.

Vehicle Quota System (VQS): This strategy is designed for cities with limited spatial capacity, such as Singapore. It controls the vehicle population through a certificate of entitlement (COE) scheme that regulates ownership based on vehicle type and engine capacity. VQS ensures a balanced load on urban roads and supports long-term traffic and environmental stability (Manasa, 2018).

Floating Car Data (FCD): FCD uses timestamped GPS and velocity data from participating vehicles to describe vehicle movement in a Lagrangian frame, unlike stationary traffic monitors that provide Eulerian views. FCD transforms vehicles into mobile sensors and enables real-time adaptive traffic management, making it an enabler for both efficiency and surveillance-supportive strategies (Runyoro & Ko, 2013).

Despite these advances, traffic lanes in both urban and rural environments are still largely treated as static infrastructure, with fixed directional configurations (n+n lanes). Urban planners tend to assume these parameters are constant in simulations and design, rarely addressing dynamic reallocation.

When recurring congestion arises, traditional remedies include costly street reconstruction, re-timing traffic lights, or introducing HOV and yellow lanes. However, such interventions do not optimize existing lane usage or account for directional imbalance-where one side of a (n+n) street may be heavily congested while the other remains underused.

In modern smart cities, the concept of Digitally Structured Lanes (DSL) addresses directional traffic imbalance by enabling real-time reconfiguration of lane assignments.

Given a total of $2n$ available lanes, the system dynamically redistributes them into directional allocations represented by vectors:

$$\mathrm{v}ec\{A\} \text{ and } \mathrm{v}ec\{B\}, \text{ where } |\,\mathrm{vec}\{\mathrm{A}\}\,| = i, \quad |\,\mathrm{vec}\{\mathrm{B}\}\,| = j, \text{ and } i + j = 2n \tag{2}$$

The goal is to achieve temporal equilibrium by adjusting *i* and *j* based on traffic flow asymmetry. Typical reconfiguration scenarios include allocations such as:

$$(i, j) \in \{(0, 6), (1, 5), (2, 4), (4, 2), (5, 1), (6, 0)\} \tag{3}$$

for $n = 3$.

These dynamic lane states replace traditional static models like (3, 3), which assume symmetric flow, and omit configurations like (1, 1), (2, 2), (4, 4), which are not effective for congestion mitigation and are excluded for scope and clarity.

The DSL concept is intended to provoke city planners to rethink traffic architecture as adaptive and programmable infrastructure. This model not only increases throughput and reduces congestion but also introduces mechanisms for emergency lane control, prioritized security routing, and adaptive lock-down enforcement in crisis scenarios.

The objective is to elevate urban intelligence by embedding real-time street flow optimization as a core stage in infrastructure development.

As part of this, our methodology integrates cellular automata modeling, specifically a modified Nagel–Schreckenberg model to simulate directional lane transformation and flow stability (Aubert et al., 2017; Nagel, 2016).

A pilot application of this DSL methodology was tested in the eastern segment of Mihajlo Pupin Boulevard in Belgrade, Serbia. This case study demonstrates how urban segments can be evaluated for dynamic lane eligibility and digitization readiness.

Figure 1 illustrates a 1,100-meter stretch of Mihajlo Pupin Boulevard where the proposed DSL simulation was conducted.

This street section was evaluated for dynamic lane transformation feasibility based on real-time directional traffic flow analysis and infrastructure adaptability

3. DATA AND METHODOLOGY

The process of implementing Digitally Structured Lanes (DSL) begins with a detailed assessment of existing street conditions-referred to as ”Stage 1” in Table 1. The goal is to determine whether specific segments are eligible for digitization, considering not only technical feasibility but also their potential to enhance overall smart city intelligence.

The methodology is explicitly designed to balance cost-efficiency, infrastructure sustainability, and strategic urban priorities. Streets identified as candidates for DSL implementation are expected to return value through: - Increased mobility intelligence, - Reduced traffic congestion and travel time, and greater resilience during high-density or emergency events.

Moreover, the redesign aligns with broader ”security-centric urban planning”. By digitising lanes, cities will gain adaptive capabilities that can support real-time emergency routing, dynamic lock-downs, and prioritised transit flows in response to security threats or disruptions.

Table 1. Proposed steps for DSL analysis and eligibility evaluation

Stage	Description
1	Identification of urban traffc hot spots where mobility effciency and security responsiveness can be enhanced through DSL;
2	Analysis of current street dynamics based on the on the field observations and modified Nagel–Schreckenberg cellular automata model supported by Monte Carlo simulations;
3	Estimation of economic and temporal losses due to congestion in the existing (static) lane configuration, derived from simulation outputs;
4	Estimation of projected savings and performance improvements using simulated DSL reconfiguration;
5	Creation of a multi-criteria decision-support matrix to assess feasibility, return on investment, and security performance trade-offs

3.1. Hot areas identification and modified Nagel–Schreckenberg model

To monitor and simulate traffic behaviour in high traffc street lanes, this study employs a modified ”Nagel–Schreckenberg cellular automaton model” (Wolfram, 2002). The selected street segment is divided into uniform spatial units called ”smartCells”, each 8 meters in length. This cell size reflects the average footprint of a passenger vehicle, including a safe following distance, as validated in previous works (Nagel, 2016).

Each vehicle occupying a smartCell operates with a speed between V0 and Vmax, with stopped vehicles assumed to have a speed of V0. The maximum number of vehicles in a lane is calculated as MaxVehicles = LaneLength/8

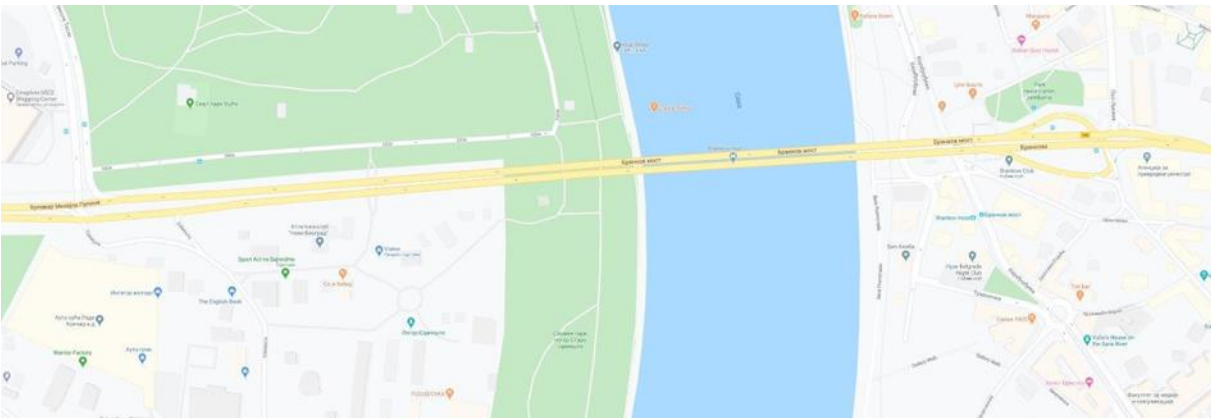

Figure 1. Segment of Mihajlo Pupin Boulevard (1,100 meters) in Belgrade, Serbia, selected for application of the DSL (Digitally Structured Lanes) simulation. (Google Maps, 2025)

A standard street lane segmentation according to modified Nagel–Schreckenberg model is illustrated in Figure 2.

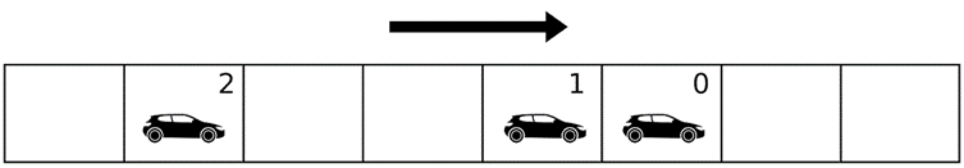

Figure 2. Street lane segmentation according to modified Nagel–Schreckenberg model

(Maksin & Ristić & Vujić, 2018)

Based on this framework, the following assumptions and structural inputs are defined for the Mihajlo Pupin Boulevard test case:

Focus is on observed "peak hour periods": 08:00–10:00, 13:00–14:00, and 17:00–19:00.

Each input point (Ai1, Ai2, Bi1, Bi2) is linked to a random generator that creates 1 vehicle every 4 to 8 seconds. During morning peaks, east to west or "North Vector" (vec {A}) experiences increased pressure. In such cases, output points (Bo1, Bo2) release vehicles randomly every 60 to 80 seconds, simulating typical congestion bottlenecks.

These inputs allow us to model "congestion dynamics, directional imbalance", and energy losses. The simulation also estimates "emissions and productivity loss" based on fuel types and average passenger density.

This model is not only a mobility optimiser but also supports "strategic simulation" for emergency lane activation, rerouting during security threats, and predictive congestion monitoring.

The framework was implemented in Python using the ‘pyspy‘ symbolic computing package (Meurer, 2021), with performance-critical components written in C++.

3.2. Existing Street State Analysis

The current state of the monitored street segment was analysed by estimating traffic volume and congestion patterns across a one-month period, focusing on four daily peak hours.

In the analysed urban area, rush hour periods are observed in the morning (08:00–10:00) and afternoon (13:00–14:00 and 17:00–18:00).

While this analysis is based on empirical observation, more precise congestion estimates could be obtained through field data collection or by leveraging Floating Car Data (FCD) techniques (Runyoro & Ko, 2013).

During congestion, an asymmetrical load distribution is observed. In morning peak hours, the "North Vector" reaches 100% capacity, while the west to east or "South Vector" (vec {B}) operates at under 50% capacity. This imbalance is mirrored in the afternoon, when the South Vector becomes saturated.

On average, this leads to 120 hours of traffic congestion per month (30 days × 4 hours/day), with only three lanes actively congested while the opposing three lanes are underutilised.

The following direct consequences of congestion are analysed in this section:

- Estimated gasoline consumed by idling vehicles;
- Productivity loss from wasted working hours;
- CO2 emissions generated.

Indirect effects such as driver stress, reduced cognitive focus, and social fatigue are outside the scope of this paper but may offer avenues for future research.

A) Estimated Gasoline Consumption

The EU has set mandatory CO2 emission reduction targets for new vehicles-130 g/km in 2015 and 95 g/km in 2021. However, real-world emissions are often higher. According to NRDC, under congested conditions at speeds below 20 km/h, emission rates rise to 544 g/mile (0.340 kg/km). This value is used for simulation estimates.

Serbian Statistical Offce data from 2017 indicates 65% of vehicles are diesel and 35% gasoline-powered. According to IEA and Eurostat reports, fuel consumption in Europe worsened in 2017–2018, with average usage at 5.1 L/100 km.

Additionally, MERN estimates that an idling 3.5L engine consumes over 2 liters/hour.

As of 2022, Serbia had one of the lowest electric vehicle penetration rates in Europe (0.04%);

B) Productivity Loss Due to Wasted Work Hours

According to Eurostat, the average hourly labor cost across EU member states is EUR 27.7. Although this figure varies significantly by country, we apply this rate for simulation consistency. Based on daily congestion patterns, the cumulative lost productivity in Belgrade's Mihajlo Pupin Boulevard segment is substantial.

C) CO_2 Emissions Summary

Assuming two passengers per vehicle, total daily congestion results in over 16,768.8 kg of CO2 emissions per month, and significant energy waste all stemming from an existing lane configuration (3+3).

3.3. Digitised street state analysis

Street lane digitisation within the Smart City framework enables dynamic reallocation of traffic capacity during rush hours. When applicable, the platform shifts one or two lanes toward the more congested direction - "North Vector" or "South Vector" - transforming the default (A3+B3) lane configuration into options such as (A2+B4), (A4+B2), or (A5+B1).

This analysis focuses on quantifying improvements in vehicular throughput under various lane adjustments. Congestion is averaged over four peak hours per day (two morning, two afternoon). Morning congestion typically results in a fully saturated "North Vector", while "South Vector" remains underutilised - mirrored during evening rush hours.

The strategic goal of lane reallocation is to reduce congestion to fewer than four daily hours by dynamically adjusting the street's lane configuration based on real-time demand.

To generalise, the dynamic lane configuration logic can be expressed as:

$$Ai + Bj, \text{ where } i + j = 6, \text{ and } i, j \in \{0, 1, ..., 6\} \tag{4}$$

This strategy allows for dynamic congestion pattern recognition and adaptive lane modelling.

3.4. Simulation model

The core simulation is built upon a modified "Nagel–Schreckenberg cellular automaton", integrated with principles from "Wolfram's cellular automata framework" (Wolfram, 2002), and enhanced through "Monte Carlo randomization" for stochastic traffic event modeling.

Key characteristics of the model:

- Each lane is divided into 8-meter smartCells to represent individual vehicle occupancy.

- Vehicles operate with discrete speed states between V0 and Vmax.
- Lane capacity is dynamically adjusted via lane reallocation policies simulated in configurations (A3+B3), (A4+B2), and (A5+B1).
- Simulation time frames span 2–8 hours, capturing transitions between congestion and equilibrium.

The simulation was implemented in the "Python 3.8", running on a "Linux Ubuntu" environment. The built-in bash random number generator (RANDOM) was used for Monte Carlo trials to simulate vehicle arrival intervals and output queue delays.

4. RESULTS AND DISCUSSIONS

This component of the research aims to quantify the economic and environmental impact of persistent congestion in static versus digitized lane configurations.

Data parameters included:

- Average hourly labor cost per worker in Europe: EUR 27.7 [EUR6],
- Fuel consumption and CO2 emission levels at low speeds: 0.340 kg/km ,
- Distribution of fuel types: 65% diesel, 35% gasoline-powered vehicles,
- Estimated idle fuel consumption rate: 0.6 L/h per liter of engine displacement.

The model computes:

- Total vehicle-hours spent/lost/vasted during congestion,
- CO_2 emissions based on idle duration,
- Economic value lost due to delayed labor output (EUR/vehicle × hours).

This analytical approach provides a replaceable and adaptable framework for evaluating Smart City strategies based on "digitized traffic lane management", with support for real-time integration via Smart Infrastructure Platforms (SIP).

Number of smartCell's in single lane counts 137, while total initial vec{A} and vec{B} capacity is 411 vehicles.

Assuming two passengers per vehicle, total daily congestion results in over "91,000 EUR in lost value", "16,768.8 kg of CO2 emissions" per month, and significant energy waste-all stemming from an existing static lane configuration (3+3).

For the Mihajlo Pupin Boulevard segment in Belgrade, the estimated annual economic loss based only on idle work hours and fuel waste and it is approximately EUR 32,787,936.00, signalling urgent need for policy and technological intervention.

Additional tables, images and code listings from simulation performed are available upon request since due the limitation of this paper had to be omitted.

5. CONCLUSION

This paper highlights urban traffic congestion as a critical barrier to sustainable mobility and quality of life in smart cities. Prolonged delays, increased fuel consumption, and elevated CO2 emissions represent direct costs, while psychological stress and opportunity loss constitute hidden burdens on the community.

Due to limited access to live sensor arrays and IoT datasets, the research was conducted using street segment observations and a custom simulation model grounded in cellular automata, specifically a modified Nagel–Schreckenberg algorithm. While constrained in scope, the model effectively quantifies the scale of inefficiencies and supports a proof-of-concept for lane digitisation strategies.

The study demonstrates that even partial lane reallocation, as part of a dynamic and responsive smart infrastructure, can significantly mitigate peak-hour congestion and improve traffic throughput.

Future research should prioritise:

- Deployment of real-time traffic sensors and Floating Car Data(FCD) platforms,
- Development of adaptive traffic flow equilibrium algorithms using extended cellular automata models,
- Validation of simulation outputs with real-world telemetry,
- Integration of strategic security considerations, including emergency lane switching and evacuation protocols.

The authors propose that Smart City governance bodies treat adaptive lane management as a core component of urban mobility intelligence, strategic security and resilience framework.

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REFERENCES

Aubert, J., et al. (2017). Smart-X: an Adaptive Multi-Agent Platform for Smart Topics. *Procedia Computer Science*, 109, 943–948. https://doi.org/10.1016/j.procs.2017.05.438

Atici, C., Ozcelebi, T., & Lukkien, J. J. (2011). Exploring user-centered intelligent road lighting design. *IEEE Transactions on Consumer Electronics*, 57(2), 788–793. https://doi.org/10.1109/TCE.2011.5955223

Bagloee, S. A., Tavana, M., Asadi, M., & Oliver, T. (2019). Is it time to go for no-car zone policies? Braess Paradox detection. Transportation Research Part A: Policy and Practice, 121, 251–264. https://doi.org/10.1016/j.tra.2019.01.021

Cohn, S. A. (2021). Hyperloop. USA. ISBN: 978-0-9725955-0-6.

Fryszman, F., Carstens, D. D. D. S., & Da Cunha, S. K. (2019). Smart mobility transition: A socio-technical analysis in Curitiba. *Int. Journal of Urban Sustainable Development*, 11(2), 141–153. https://doi.org/10.1080/19463138.2019.1630414

Runyoro, A. A. K., & Ko, J. (2013). Real-time road traffic management using floating car data. *International Journal of Fuzzy Logic and Intelligent Systems*, *13*(4), 269-276. https://doi.org/10.5391/IJFIS.2013.13.4.269

Knuth, D. E. (1998). The Art of Computer Programming (3rd ed., Vol. 1). Addison-Wesley.

Lutz, M. (2013). Learning Python (5th ed.). O'Reilly Media.

Manasa, P. (2018). Singapore model of smart city: A solution to growing urbanisation. International Journal of Research in Social Sciences, 8(1). http://www.ijmra.us

Maksin, M., Ristić, V., & Vujić, A. (2018). Application of the IoT smart city technology in transport security improvement. In Proceedings of the 17th International Conference – International University Travnik (Vol. 1). Travnik, Bosnia and Herzegovina.

Meurer, A., et al. (2021). SymPy: Symbolic computing in Python. https://doi.org/10.7717/peerj-cs.103

Maldonado Silveira Alonso Munhoz, P. A., da Costa Dias, F., Kowal Chinelli, C., Azevedo Guedes, A. L., Neves dos Santos, J. A., da Silveira e Silva, W., & Pereira Soares, C. A. (2020). Smart mobility: The main drivers for increasing the intelligence of urban mobility. *Sustainability*, 12(24), 10675. http://dx.doi.org/10.3390/su122410675

Nagel, K., & Schreckenberg, M. (1992). A cellular automaton model for freeway traffic. Journal de Physique I, 2. http://www.ptt.uni-duisburg.de/fileadmin/docs/paper/1992/origca.pdf

Nagel, K., & Schreckenberg, M. (2016, January 15). North Rhine-Westphalia's OLSIM traffic forecasting system. Autobahn NRW. http://www.autobahn.nrw.de/

Rubinstein, R. Y., & Kroese, D. P. (2008). Simulation and the Monte Carlo Method (2nd ed.). Wiley.

Soriano, F. R., Samper-Zapater, J. J., Martinez-Dura, J. J., Cirilo-Gimeno, R. V., & Plume, J. M. (2018). Smart mobility trends: Open data and other tools. *IEEE Intelligent Transportation Systems Magazine*, 10(2), 6-16. https://doi.org/10.1109/MITS.2017.2743203

Stroustrup, B. (2000). The C++ Programming Language (3rd ed.). Addison-Wesley.

Toh, C. K., Cano, J., & Manzoni, P. (2020). Advances in smart roads for future smart cities. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 476(2233), 20190439. https://doi.org/10.1098/rspa.2019.0439

Umedu, T., et al. (2010). An intervehicular-communication protocol for distributed detection of dangerous vehicles. IEEE Transactions on Vehicular Technology, 59(2), 627–637. https://doi.org/10.1109/TVT.2009.2035041

Vujic, A. (2014). Smart parking in smart city. In Proceedings of the ICAIIT 2014 – International Conference on Applied Internet and Information Technologies (p. 292). Zrenjanin, Serbia. https://aiitconference.org/archive/Proceedings_AIIT2014.pdf

Wolfram, S. (2002). A new kind of science. Wolfram Media.