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Traffic Optimization with Smart Traffic Lights: An Overview of Algorithms and Implementations

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***Abstract*—This paper explorers the algorithms and real-time deployments for smart traffic lights from 2015–2025. It introduces a taxonomy of control paradigms (centralized optimization, decentralized heuristics, max-pressure, model predictive control) and learning methods, with emphasis on single- and multi-agent reinforcement learning. It compares coordination strategies across intersections, simulation-to-reality transfer and federated training workflows, and multiobjective formulations balancing delay, emissions, safety, and priority for public transport and emergency services. Evidence from pilots and city-scale platforms is compiled to quantify travel-time and throughput gains. A benchmarking map classifies approaches by data, optimization strategy, and maturity of adoption, exposing gaps in generalization, rare-event resilience, and interpretability. The paper closes with guidance on hybrid edge–cloud architectures, standardized interfaces, and reproducible evaluation protocols covering heterogeneous networks and operating conditions.**

***Keywords*—edge computing, multi-agent reinforcement learning, smart traffic lights, traffic signal control, V2X communication.**

I. Introduction

Urbanized areas around the world are suffering from a growing congestion problem, which leads to significant economic and environmental losses. In 2014, traffic jams cost the United States more than $160 billion in lost productivity and wasted 3.1 billion gallons of fuel. In the European Union, the annual cost of congestion is estimated at about 1% of Gross domestic product (GDP). Optimizing their work cycles is key to easing traffic. Traditional traffic light management methods (such as fixed timers or classic adaptive systems) rely on preset plans and limited traffic information. With the advent of smart traffic lights – AI-driven devices that adapt dynamically – over the past decade a significant advances in the ability to optimize traffic in real time is seen. This report provides an in-depth overview of all the major algorithms, technologies and implementations from the period 2015-2025 related to intelligent traffic light management. reinforcement learning and multi-agent systems to swarm intelligence, edge computing, centralized and decentralized management, and more. Also, the architectures, sensors, and communication protocols used (e.g. V2X) are analyzed, as well as real implementations around the world. Finally, the main trends, a comparative analysis of methodologies, the most cited publications and the leading researchers in this field are outlined.

II. Methodological Approaches for Intelligent Traffic Light Control

A. Reinforcement Learning

One of the most dynamically evolving approaches to traffic light optimization is reinforcement learning (RL), in which an intelligent agent (e.g. traffic light controller) learns through trial and error to select optimal actions (e.g. when to change the light), maximizing a certain reward – usually a derivative of travel time, queue lengths or vehicle delays. – using deep neural networks that can approximate value functions or directly select an action based on complex input data. The first successful applications appeared around 2015–2016; for example, Li et al. [1] demonstrate how a deep Q-neural network can be trained to manage signaling plans at an intersection, outperforming a fixed circuit. Compared to traditional optimization approaches, which require a simplified mathematical model of traffic, reinforcement learning methods learn directly from the data and can reflect complex real-world factors (e.g., the reaction of different drivers, the presence of pedestrians, etc.) without making simplifying assumptions. This allows for more effective adaptation to the changing environment.

In the literature of the last decade, there has been an explosion of research applying deep traffic light control OPs. Various algorithms have been developed – from classic Deep Q-Learning through actor-critic methods to federated reinforcement learning. Particular attention shall be paid to the choice of remuneration function (e.g. minimizing cumulative waiting times, the number of shutdowns or emissions per CO_2) and to the sustainability of the policies learned in real-world conditions. A 2021 review study (Wei et al. [2]) covers 26 years of development of traffic management OPs and notes the significant progress of modern RL methods compared to older ones. However, challenges such as dealing with rare events (e.g. accidents), explainability of decisions and safe training in a real environment remain relevant. To overcome them, techniques such as training in a simulation environment with subsequent transfer to reality and the development of more complex models of state (e.g., graph neural networks that take into account spatial dependencies between multiple intersections) are being explored.

B. Multi-Agent Systems and Distributed Management

Multi-agent approaches consider a large transport network as a set of interacting intelligent agents – each

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traffic light is an agent that makes local decisions and communicates with neighboring ones. This approach aims at coordination between intersections so as to avoid the so-called traffic jams. "local optimality" at the expense of systemic inefficiency. A pioneering study in this area is the MARLIN-ATSC (Multi-Agent Reinforcement Learning for Integrated Network of Adaptive Traffic Signal Controllers) [3] method proposed by El-Tantawy and Abdulhai. Through multi-agent reinforcement learning, each traffic light learns a policy that optimizes its traffic while implicitly taking into account the effect on neighboring intersections – i.e., overall network optimization is achieved. MARLIN-ATSC has been validated in a simulation on a network in downtown Toronto with promising results and was patented in 2017 (U.S. Patent 9818297) [4].

Another influential system developed at Carnegie Mellon University is SURTRAC (Scalable Urban Traffic Control) [7], which uses a decentralized multi-agent approach. Each traffic light in SURTRAC locally optimizes its signaling schedule through a dynamic planning algorithm, and neighboring intersections exchange information about projected flows to form "green waves" when needed. Thanks to this approach, the pilot implementation of SURTRAC in Pittsburgh (9 traffic lights in the area East Liberty) achieves over 25% reduction in travel time and about 40% reduction in red light for drivers. Characteristic of multi-agent systems such as SURTRAC is decentralized coordination – decisions are made at the intersection level in real time, which leads to higher responsiveness to local changes and eliminates a single point of failure in the system. Recent research combines multi-agent OP with deep learning – for example, algorithms such as PressLight[11] and CoLight[12] use careful mechanisms or graph neural networks to improve coordination between multiple traffic lights in large networks. The results show better scaling and load management compared to single-agent RL solutions.

C. Centralized and decentralized management

Control architecture is a key factor in smart traffic light systems. Centralized systems collect information from multiple intersections in the city in one place (cloud server or traffic center) and calculate the optimal settings for all traffic lights collectively. Such an approach has the potential to find a globally optimal solution for the distribution of "green waves" throughout the network, but requires reliable communications and significant computational resources in real time. An example of a centralized system is the City Brain project in Hangzhou, China, a cloud-based platform developed by Alibaba that analyzes real-time data from cameras, vehicle GPS and other sources, and manages more than 100 traffic lights from a central AI "core." The results are impressive: only a year after the implementation of the so-called. City Brain reduced the average wait time by over 15% in the pilot zones, with the city climbing from 5th to 57th place in the "most congested city" indicator in China. Centralized control also facilitates prioritization – for example, the system in Hangzhou automatically gives priority to ambulances and fire brigades, halved the time for an ambulance to arrive in an emergency.

In contrast, decentralized strategies rely on local intelligence at each intersection. Each controller independently decides when to extend or change the signal, based on its local sensors and possibly limited communication with neighboring controllers. This allows for a very fast response to sudden changes (e.g. queue build-up), as there is no need to wait for a "top" direction. They are easier to expand – a new traffic light can be added to the system without having to change a central algorithm. On the other hand, the lack of global coordination can sometimes lead to suboptimal solutions (e.g. one section being preferred by all traffic lights in favor of a parallel artery). that corrects long-term trends or goals. In some cities, traditional adaptive systems (e.g. SCOOT in London or SCATS in Sydney) function precisely as a centralized coordination of local adaptive controllers: the center periodically updates the optimal differences (offsets) between traffic lights on the main arteries, but leaves each intersection to adjust according to local traffic

D. Edge Computing and Smart Endpoints

Improvements in hardware in recent years have enabled edge computing – performing complex calculations on site, close to the data source (at the intersection itself), rather than in a remote center. With smart traffic lights, this means that each traffic light column can be equipped with a compact computing device (e.g. NVIDIA Jetson [15]), which locally processes data from cameras and sensors and executes AI control algorithms. This architecture reduces latency – decisions to switch lights are made in milliseconds, with no delay from data transfer to the cloud. Also, sensitive raw data (such as video) can be processed on-site, with only aggregated or anonymized data sent to the central server, which improves cybersecurity and privacy.

For example, the startup NoTraffic implements a platform where each intersection has a local AI controller with cameras and radars running on an NVIDIA Jetson platform (achieving ~40x acceleration in image processing relative to CPU). A combination of Edge and Cloud enables both rapid local response and global strategy optimization based on aggregated data. In addition, having computing power on site makes it easier to deploy advanced sensors: for example, sophisticated computer-visual models can count pedestrians and cyclists in real time at the intersection itself, rather than sending video to a center for analysis.

E. Sensors and V2X communication

Smart traffic lights use a variety of sensors to perceive the environment. Traditionally, they rely on inductive loops built into the road surface that detect passing vehicles. Modern systems add video cameras with computer vision, lidar and radar sensors that can assess the number of waiting cars, their speeds, the presence of pedestrians, etc. For example, the NoTraffic system uses a combination of optical cameras and radars mounted at each traffic light to "see" the full picture of traffic from all directions. In addition, Vehicle-to-Everything (V2X) communication technologies – direct wireless data exchange between vehicles and infrastructure – are also introduced. In V2X, vehicles can send information about their location, speed and direction to traffic lights, and the traffic light responds with information about the remaining time up to green/red (Signal Phase and Timing (SPaT). or newer via cellular 5G-V2X) allows for more precise control – for example, traffic lights can "know" how many cars are approaching earlier even before they are within range of local sensors. In pilots such as the Multi-modal Intelligent Traffic Signal System (MMITSS)[13] in the U.S. V2I, communication is used to balance the priorities of different actors – prioritizing buses and emergency vehicles without undue delay for others.

Some automakers are already taking advantage of V2I infrastructure: for example, Audi models in certain cities receive information from connected traffic lights and show the driver a countdown to a green light, which can reduce aggressive departure. In terms of traffic optimisation, V2X allows for the introduction of adaptive speed limits or recommendations to drivers (the so-called. "green wave advisor"), so that if they follow a recommended speed, they fall on green without stopping. With the increase in the equipment of cars with V2X modules, smart traffic lights will have an even richer set of real-time data, which will further improve their driving models. An important aspect is the standardization of communication protocols (IEEE, ETSI, etc. work on data exchange standards such as SPaT, MAP, BSM, etc.) so that different car brands and infrastructure can "speak the same language". In countries such as China, urban intersections are massively equipped with 5G transceivers, which is already showing an effect in projects such as Hangzhou City Brain [5] and contributes to a more stable and faster connection between components.

F. *Swarm intelligence and evolutionary algorithms*

In addition to machine learning methods, a number of metaheuristic approaches inspired by nature have also been used in traffic optimization - the so-called "Traffic Optimization". swarm intelligence. These include algorithms such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), evolutionary strategies and genetic algorithms. What they have in common is that through imitation of the collective behavior of insects or through evolutionary simulations, a close to optimal solution to a complex problem is sought – in this case, the adjustment of traffic light cycles. For example, ACO can be used to search for optimal phase lengths, with "ants" building solutions and gradually improving them based on pheromone feedback (the target function can be, for example, the average deceleration of cars). The PSO, in turn, treats each potential set of traffic light parameters as a particle in the decision space and moves the particles on a collective experience basis to find the optimum.

These approaches are attractive because they do not require the construction of a differential traffic model – they work directly with simulation or data, optimizing a black box. There are studies that have shown that swarm algorithms can significantly improve traffic at least in simulation conditions. For example, the application of a genetic algorithm to 24 intersections in the city of Zaragoza [6] has led to a noticeable reduction in congestion at peak hours (in a simulation). However, computational complexity is computationally complex – to find a good solution, it often takes hundreds to thousands of iterations, making them challenging for direct real-time application. That's why some researchers use them in hybrid schemes – for example, they generate initial good plans, which are then fine-tuned by faster algorithms or used to train reinforcement systems. However, swarm intelligence remains an active research area in the context of the smart city, including for traffic optimization, due to its flexibility and ability to find unconventional solutions.

G. *Other approaches and hybrid solutions*

There are other traffic light optimization methodologies that complement the above-mentioned. Phase logic and fuzzy logic systems have been studied since before the deep learning boom – "if-to" rules are drawn up (for example, "if the queue in the north exceeds 10 cars and the southern queue is empty, extend the northern green phase"). Such systems can be effective in specific scenarios and are easily explained, but usually require manual adjustment by experts and do not scale well at many interconnected intersections. Predictive Model Control (MPC) – it uses an explicit traffic model [14] (e.g. flow equations) and an optimization algorithm that solves the optimal control problem for a horizon of a few minutes ahead at each step, then slips in time. MPC can include constraints (e.g. cycle lengths, maximum queues) and run in real-time with sufficiently fast algorithms, but its accuracy depends heavily on the quality of the traffic model.

Among the decentralized algorithms, it is worth mentioning the so-called. Max-pressure policy – a relatively simple local algorithm from the theory of network traffic, which at any time gives a green light to those directions for which the difference ("pressure") between the length of the queue at the entrance and exit of the intersection is the greatest. It has been theoretically proven that under certain conditions this algorithm stabilizes the network of queues close to optimal. combining it with training or adapting it for situations with uncertainty in the data.

Multi-purpose optimizations are also becoming more and more relevant. Instead of only minimizing latency, cities often want to optimize both pollutant emissions and safety. This requires balancing conflicting goals – for example, minimum latency can conflict with minimum emissions. In the literature, there are solutions such as Pareto optimization, where compromise settings are sought. new factors for consideration are also emerging (e.g. smart traffic lights that communicate with autonomous cars and jointly plan their passage through the intersection without stopping).

III. REAL SYSTEMS AND IMPLEMENTATIONS AROUND THE WORLD

Over the past decade, numerous cities have experimented or implemented parts of the described technologies, showing real improvements. Pittsburgh (USA) is one of the pioneers – the SURTRAC system [7] was launched as a pilot in 2012 and by 2015 covered dozens of intersections. The results from Pittsburgh show a 25% shorter travel time on average and a 40% reduction in traffic light stays. The success of the pilot led to the creation of a startup (Rapid

Flow Technologies) to commercialize the technology, and in the 2020s SURTRAC was acquired and implemented by the company Miovision. expanding its scope to other cities.

Since the implementation of City Brain in 2016-2017, the city has seen a 15% reduction in delays in pilot areas and a significant improvement in traffic speed during peak hours. Even more impressively, Hangzhou falls from the top places in terms of traffic congestion, dropping from 5th to 57th place in terms of traffic congestion in the ranking of Chinese cities. And for other aspects: automatic traffic light control reduces the need for police officers to direct traffic by hand at peaks, and also allows for priority for emergency vehicles – statistics show that the response time of ambulances in some areas has dropped by 50% thanks to smart traffic lights. The success in Hangzhou led to the concept being copied in other cities such as Suzhou, Macau, etc.

In Israel and Brazil, tech giant Google is testing AI-based traffic light optimization in real-world conditions [8]. In a pilot with four intersections in Israel (Tel Aviv and Haifa), their software managed to reduce wait times and fuel consumption by 10–20%. Based on these results, in 2022, Google announced a partnership with the city of Rio de Janeiro to implement their traffic light management system, with local authorities expressing high expectations for traffic relief. While there is some skepticism from transportation engineers about whether a software approach will easily cover all the practical nuances, these pilots demonstrate the industry's interest in solving traffic problems through artificial intelligence.

Israel's NoTraffic [9] has piloted deployments in several U.S. cities (e.g., Tucson, Arizona, and Vancouver, Canada), showing significant improvements. In Tucson, a system with over 80 traffic lights equipped with an AI camera platform achieves up to a 46% reduction in rush hour delays and a 23% average reduction in travel time in the pilot corridor. Passing red (red violations) after implementation – evidence that better management also increases safety. On the campus of the University of British Columbia, where NoTraffic is working with a telecommunications company for 5G connectivity, up to 40% reduction in delays for pedestrians and a significant reduction in average waiting times for cars has been achieved. The NoTraffic platform has already been implemented (or in the process of being implemented) at over 200 intersections in 35 US states, making it one of the most widely used private solutions.

Various countries are also betting on updating the classic adaptive systems. Sydney (Australia) continues to develop SCATS [10], a system that has been in operation for decades, but now integrates camera data and V2X for better adaptability. London with SCOOT covers almost all traffic lights in the city and regularly updates its algorithms. Dubai has announced a "smart cities" strategy incorporating traffic AI and is testing smart traffic lights connected to central control, which adapt cycles in real time according to traffic and give priority to buses and emergency vehicles. In the Netherlands, there are also pilot projects with the so-called. "Smart frames" – traffic lights that communicate directly with bicycles and cars to optimize the flow on bike lanes and intersections.

Along with urban implementations, patented solutions are also emerging. For example, the already mentioned MARLIN-ATSC technology [3] is patented in the United States, as are the algorithms behind SURTRAC (patents US 9,159,229 of 2015 and US 9,830,813 of 2017 for adaptive management of urban signals). The European Patent Office has also published patents for deep learning applications at traffic lights – e.g. EP 3782143 B1 (2021) offers a multi-model deep RL solution for intersection traffic optimization. These patents show the interest in commercializing scientific advances and the willingness of companies and universities to protect the intellectual property of smart traffic algorithms

IV. Key Trends and Benchmarking

The analysis of the various approaches allows us to highlight several main trends in the development of smart traffic lights in 2015-2025:

- Introduction of artificial intelligence and deep learning in particular: From a relatively niche topic at the beginning of the period, deep reinforcement learning has become the dominant research direction for optimization of signal management. The reason for this is the availability of ever larger data sets (from sensors, GPS of cars, cameras) and increasing computing power. RL systems have proven that they can handle traffic dynamics better than static algorithms by learning directly from interaction with the environment. The trend is towards increasingly complex models – using deep neural networks to assess the state of the network or to coordinate between intersections.
- Decentralization and edge processing: There is a shift away from fully centralized solutions (which were standard in older adaptive systems) towards distributed architectures. Even when there is a central "brain", it often serves for training or global coordination, while operational decisions are made locally at the crossroads. This brings advantages in speed and reliability, especially in case of temporary loss of connection. The rise of edge computing devices supports this trend – Cities can afford to equip hundreds of intersections with smart controllers at an affordable price, rather than investing in a huge central supercomputer.
- Communication integration (V2X): Connectivity between cars and infrastructure has gone from an experimental technology to a reality on the road. In recent years, many cities have installed DSRC or 5G receivers at traffic lights, and car companies are adding V2X modules to their vehicles. This means that smart traffic lights will have much more complete information – not just when a car arrived at the stop line, but also how many cars are approaching, at what speed, even what type they are (e.g. bus, truck, car). Such information allows for more far-sighted optimisation, reduced stops and even personalised control (e.g. extending the green light if a city bus is approaching with a delay). Projects like the one in Vancouver with 5G-connected traffic lights show that real benefits are

already being achieved from this integration. It is expected that with the advent of autonomous cars (which by definition will be V2X-compatible), this trend will intensify even more.

- Multi-purpose and sustainable solutions: It's no longer just about optimising the flow of cars – the goals of governance have expanded. Cities value environmental performance (low emissions, less noise), prioritise public transport and vulnerable actors (pedestrians, cyclists), which has led to research towards multi-lens functions and settings that seek balance. For example, RL agents, who include emissions and comfort components in their award, except travel time. Also, the theme of sustainability also manifests itself as the search for solutions that are stable in rare events and can adapt to unforeseen situations (such as catastrophes or major public events). Some works are experimenting with generalized agents that can transfer knowledge from one intersection to another, or with federated learning, where models trained in different cities exchange knowledge without sharing raw data.
- Gradual introduction to real-world applications: Despite the wealth of academic solutions, their practical implementation requires time, testing and trust on the part of municipalities. The trend of 2015-2025 is from small pilot projects to larger deployments. Initial successes (such as those in Pittsburgh and Hangzhou) have shown that smart traffic lights can bring tangible effects, leading to increased funding and interest – both from the public sector, and by tech giants and startups – to deploy these systems. Currently now is the stage where individual neighborhoods or corridors in major cities around the world are already managed by AI systems. The scale is expected to grow in the coming years – for example, New York City is planning adaptive AI control at hundreds of intersections in Manhattan, and cities such as Singapore and Dubai are putting smart traffic lights as a key element of their "smart cities" programs.

For a clearer summary, Table 1 presents a comparative classification of the different traffic light traffic optimization approaches, according to the technologies used, data types, optimization strategies and their degree of actual implementation.

TABLE I

CLASSIFICATION OF THE MAIN APPROACHES TO TRAFFIC MANAGEMENT THROUGH SMART TRAFFIC LIGHTS ACCORDING TO THE TECHNOLOGY USED, DATA TYPE, OPTIMIZATION STRATEGY AND DEGREE OF IMPLEMENTATION

Approach	Technology used	Input data type	Optimization strategy	Implementation Rate
Traditional adaptive control (e.g. SCATS, SCOOT)	Rules based on pre-set plans; Deterministic algorithms	Inductive loops, traffic detectors (volume, lane occupancy)	React to changes by switching between pre-calculated plans; Optimization of phase differences (offsets) in a central controller	Widely implemented in many cities (since the 1970s); Constantly improved (real systems)
Centralized optimization (Model-predictive control, offline optimization)	Classical optimization methods (linear/ dynamic programming, MPC) in a central server	Aggregated urban traffic data (load by sections, routes, cycles)	Periodic solution of an optimization problem for the entire network; global target (min. total delay, etc.)	Limited practical application alone; Used in combination with local systems (pilots, simulations)
Decentralized local government (напр. max-pressure, SURTRAC)	Local algorithms in controllers (heuristics, thirsty algorithms or dynamic scheduling)	Local sensors at the intersection (queue counters, CCTV cameras); sometimes exchanges with neighbors	Each intersection optimizes its own schedule according to local criteria (e.g. queue balance); coordination through communication with neighbouring controllers	Real deployments in several cities (pilots and partial coverage); proven performance in medium-sized networks (e.g. 50 traffic lights)
Reinforcement Training (Single Agent)	Deep neural networks (DQN, DDG, etc.) trained by RL; require GPUs for training	Data on the traffic status at the intersection (queue lengths, car counter; maybe cameras, radars)	Studies politics through trial and error, maximizing reward (e.g., delay); Training first in simulation, then application in reality	Mostly academic research and simulations; limited pilot tests at real intersections (e.g. 4 intersections in Israel)
Multi-Agent Reinforcement Learning	Combination of RL agents for each intersection; sometimes graph neural networks for coordination	Local data + information exchanged between agents (e.g. forecast flows to neighbors)	Distributed training – agents learn in parallel, with shared reward or coordinated through communication; Target – Network Level Optimum	Simulation studies of large networks; pilot implementations (e.g. MARLIN-ATSC in a simulation of downtown Toronto); not yet massively implemented on the ground
Swarm intelligence (ACO, PSO, GA, etc.)	Nature-inspired metaheuristic algorithms; Simulations needed to evaluate decisions	Traffic statistics or network simulation model; Historical scenarios	Iterative optimization: generation of multiple candidate plans, selection and combining/ mutations until approaching a good solution (minimizing a selected target function)	Applications mainly in research and offline optimization; is not directly used in real management (due to computational requirements); Used when setting up other systems
Edge AI controllers (decentralized edge computing)	Embedded AI devices at the intersection (GPU-based platforms; Nvidia Jetson, etc.)	Local raw sensor data (video, radar) processed on site; Minimal dependency on a center	Real-time local decision-making; possibly communication with the cloud to unify data and train models	Up-to-date technology – pilot deployments (e.g. NoTraffic in the USA, projects in Europe); expected expansion given initial successes
Cloud AI platform (centralized "city brain")	Big Data platforms, cloud servers with AI (Hadoop, GPU clusters, etc.)	Urban information platforms: integrated data from hundreds of cameras, GPS, sensors; historical and real-time	Central AI analyzes traffic comprehensively and sends optimal settings or recommendations to traffic lights; can use a combination of methods (optimization, ML)	Real implementations in megacities (e.g. Hangzhou City Brain, Alibaba Cloud); it is also used for other urban tasks besides traffic; trend mainly within Smart City projects

V. Conclusion

The development of smart traffic lights over the past 10 years demonstrates the enormous potential of new technologies to tackle an old urban problem – traffic jams. The variety of approaches – from neural networks that learn to "adjust" traffic lights on their own, to swarms of virtual ants looking for optimal solutions, to urban "brains" in the cloud that see every intersection – shows that there is no single solution, but rather a set of tools that cities can apply according to their context.

The main trends point to smarter, connected and adaptable systems. Cities are gradually upgrading existing infrastructure (sensors, controllers) with layers of artificial intelligence. The initial results are encouraging: a significant reduction in delays, fewer stops, lower emissions and even increased safety at intersections. The introduction of V2X communication opens the way to even more global optimization – in connection not only with traffic lights and cars, but also with a complete ecosystem of urban mobility, where cars, traffic lights, public transport and pedestrians act in sync.

Of course, the challenges remain. Greater reliability and resilience of these systems are needed – they must be proven in all circumstances (road accidents, extreme weather conditions, cyberattacks). Also, the issue of trust – municipalities and citizens must accept that artificial intelligence makes decisions about traffic, which requires transparency and the possibility of human control when needed. to ensure that heterogeneous actors can work together seamlessly.

In conclusion, the period 2015-2025 laid the foundations for a future transport ecosystem in which traffic lights will not just be passive devices at intersections, but active, intelligent actors in traffic management. Ongoing scientific research, supported by increasingly large-scale real-world experiments, gives confidence that the vision of a congestion-free city – with optimized, safe and environmentally friendly traffic – is achievable with the help of smart traffic lights.

References

[1] L. Li, Y. Lv and F. -Y. Wang, "Traffic signal timing via deep reinforcement learning," in IEEE/CAA Journal of Automatica Sinica, vol. 3, no. 3, pp. 247-254, 10 July 2016, doi: 10.1109/JAS.2016.7508798.,

[2] Wei, Hua & Zheng, Guanjie & Gayah, Vikash & Li, Zhenhui. (2019). A Survey on Traffic Signal Control Methods. 10.48550/arXiv.1904.08117.

[3] S. El-Tantawy, B. Abdulhai and H. Abdelgawad, "Multiagent Reinforcement Learning for Integrated Network of Adaptive Traffic Signal Controllers (MARLIN-ATSC): Methodology and Large-Scale Application on Downtown Toronto," in IEEE Transactions on Intelligent Transportation Systems, vol. 14, no. 3, pp. 1140-1150, Sept. 2013, doi: 10.1109/TITS.2013.2255286.

[4] S. El-Tantawy and B. Abdulhai, "Multi-agent reinforcement learning for integrated and networked adaptive traffic signal control," U.S. Patent 9,818,297 B2, Nov. 14, 2017. https://patents.google.com/patent/US9818297B2/en

[5] Bai, Ou & Shi, Yijun & Wu, Fuhua. (2025). Pioneering the Post-Smart Cities Paradigm in Urban Innovation Ecosystems Governance: A Case Study of Hangzhou City-Brain Initiative. Urban Policy and Research. 10.1080/08111146.2025.2456258.

[6] Sanchez-Medina, Javier & Galan-Moreno, Manuel & Rubio, Enrique. (2010). Traffic Signal Optimization in "La Almozara" District in Saragossa Under Congestion Conditions, Using Genetic Algorithms, Traffic Microsimulation, and Cluster Computing. Intelligent Transportation Systems, IEEE Transactions on. 11. 132 - 141. 10.1109/TITS.2009.2034383.

[7] Smith, Stephen F., et al. SURTRAC: Scalable Urban Traffic Control. Jan. 2013, doi:10.1184/R1/6561035.V1.

[8] Z. Stub, "In Israel, Google tests AI tech to better time traffic lights," The Times of Israel, Oct. 6, 2021. [Online]. Available: https://www.timesofisrael.com/google-tests-ai-tech-to-better-time-traffic-lights-in-israel/

[9] NoTraffic, "AI Mobility Platform for intelligent traffic management," Accessed: Jun. 25, 2025. https://www.notraffic.com/

[10] Slavin, Courtney & Feng, Wei & Figliozzi, Miguel & Koonce, Peter. (2013). A Statistical Study of the Impacts of SCATS Adaptive Traffic Signal Control on Traffic and Transit Performance. Transportation Research Record Journal of the Transportation Research Board. 2356. 117-126. 10.3141/2356-14.

[11] Wei, Hua & Chen, Chacha & Zheng, Guanjie & Wu, Kan & Gayah, Vikash & Xu, Kai & Li, Zhenhui. (2019). PressLight: Learning Max Pressure Control to Coordinate Traffic Signals in Arterial Network. 1290-1298. 10.1145/3292500.3330949.

[12] Hua Wei, Nan Xu, Huichu Zhang, Guanjie Zheng, Xinshi Zang, Chacha Chen, Weinan Zhang, Yanmin Zhu, Kai Xu, and Zhenhui Li. 2019. CoLight: Learning Network-level Cooperation for Traffic Signal Control. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM '19). Association for Computing Machinery, New York, NY, USA, 1913–1922. https://doi.org/10.1145/3357384.3357902

[13] K. Ahn, H. Rakha, and D. K. Hale, "Multi-Modal Intelligent Traffic Signal Systems (MMITSS) impacts assessment.", Virginia Tech Transportation Institute, Blacksburg, VA, USA, Tech. Rep. FHWA-JPO-15-238, 2015

[14] Lin, Shu & De Schutter, Bart & Xi, Yugeng & Hellendoorn, Hans. (2010). Model Predictive Control for urban traffic networks via MILP. Proceedings of the 2010 American Control Conference, ACC 2010. 2272 - 2277. 10.1109/ACC.2010.5530534.

[15] Scraba, A. (2025). NoTraffic Reduces Road Delays, Carbon Emissions with NVIDIA AI. NVIDIA Blog.