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Review

Innovative Tools to Contrast Traffic Pollution in Urban Areas: A Review of the Use of Artificial Intelligence

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Abstract: Overtraffic is one of the main keys to air pollution in urban areas. The aim of the present work is to review the approaches and explore the potentiality of AI in reducing traffic pollution in urban areas, ranging over three main areas: the optimization of traffic lights timing to reduce delays, the use of AI-powered drones to monitor pollution levels in real-time, and the use of fixed AI-based sensors to detect the levels of pollutants in the air with the use of AI models to identify patterns in the collected data and predict air quality in near-real time. Some attention was also dedicated to possible problems arising from privacy protection and data security, and the case study of the Piemonte area and of the city of Turin in the north–west of Italy is presented: the current situation is depicted, and possible local future applications of AI are explored. The use of AI has proven to be very promising in all three areas, particularly in the field of optimization of traffic lights' timing and coordination in increasingly larger traffic networks.

Keywords: traffic pollution; artificial intelligence; urban areas; traffic lights; drones; air quality sensors

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Citation: Robotto, A.; Bargero, C.; Marchesi, L.; Racca, E.; Brizio, E. Innovative Tools to Contrast Traffic Pollution in Urban Areas: A Review of the Use of Artificial Intelligence. *Air* **2024**, *2*, 402–418. https://doi.org/10.3390/air2040023

Academic Editor: Alan W. Gertler

Received: 4 September 2024
Revised: 7 November 2024
Accepted: 8 November 2024
Published: 30 November 2024

1. Introduction

Disruptive technologies such as big data, artificial intelligence (AI), the Internet of Things (IoT), or cloud and edge computing are transforming all economic sectors, including mobility and transportation: highly automated vehicles governed by artificial intelligence algorithms, able to interpret dynamic situations on the road and make real-time driving decisions, learning and becoming smarter; new vehicle manufacturing processes using advanced materials, much less heavy and more resistant, which reduce emissions while increasing safety and comfort. A literature review can be found in the work of [1].

According to experts, the concept of artificial intelligence is evolving, but four main features can be identified:

- ability to learn;
- ability to adapt;
- ability to replicate and predict;
- ability to improve existing processes.

The application of artificial intelligence to urban policies can bring a number of benefits that improve efficiency, safety, and sustainability. Some studies have shown that the use of AI is correlated to a reduction in air pollution, with particular reference to $PM_{2.5}$ and SO_2, by facilitating improvements in energy structures, energy efficiency, and digital infrastructures [2].

AI is also emerging as a transformative force across various industries, and transport systems are no exception. In particular, as far as the transport sector is concerned, AI will revolutionize both the public and private sectors, with challenges in planning and organization. By leveraging AI, cities can address traffic congestion, improve safety, and reduce environmental impacts, making urban mobility more sustainable and efficient.

Traffic congestion is a pervasive problem in many cities, leading to increased travel times, fuel consumption, and emissions. Traffic congestion is also an economic problem; it has been shown that the USA spent over 115 billion dollars to face traffic congestion in 439 urban areas, just in 2010 [3].

AI has enormous potential to improve traffic flow, both in urban areas and on wider road networks. In fact, AI can help autonomous vehicles find available parking spaces more efficiently, reducing the time spent searching for a spot and the traffic generated by this activity. Regarding logistics, the predictive intelligent tools can reduce delivery times and transport costs by analyzing delivery data, optimizing vehicle routes, and improving supply chain efficiency. These are just a few examples of how artificial intelligence can help streamline traffic. Another example is the so-called adaptive traffic lights, also known as intelligent traffic lights, an innovative solution for optimizing traffic flow and reducing congestion. Unlike traditional traffic lights, which operate on fixed, pre-set timings, adaptive traffic lights use artificial intelligence and sensors to dynamically change the time cycle, following the incoming traffic.

AI technologies are then transforming traffic management by providing tools for real-time monitoring, predictive analysis, and dynamic control of traffic systems. Machine learning and predictive analytics help forecast and manage traffic flow, while computer vision and image processing enable real-time incident detection and traffic monitoring. IoT and sensors provide comprehensive data on traffic conditions, and data analytics and big data facilitate the analysis of these data to optimize traffic management strategies. Together, these technologies offer a promising solution to the challenges of urban traffic congestion, safety, and environmental impact, for example, adjusting the timing of green, yellow, and red lights based on real-time traffic conditions. A comprehensive review of the use of AI in transport can be found in [4].

Implementing these technologies requires significant investment in infrastructure and vehicles, but the potential benefits in terms of reducing traffic, improving road safety, and reducing pollution are enormous. Artificial intelligence is being used by several cities worldwide to enhance traffic management through experimentation or implementation. Here, a few examples are reported:

- Pittsburgh has implemented the SURTRAC system, which uses AI to optimize traffic light timing in real time, reducing travel times and emissions [5].
- Los Angeles uses an intelligent traffic light system that adapts to traffic flow, improving fluidity and reducing congestion [6–8].
- Singapore uses AI to monitor traffic and predict congestion, enabling timely interventions to improve circulation [9].
- In London, Transport for London uses AI to analyze traffic data and optimize the management of the road network and public transport [10].
- Hangzhou has implemented the "City Brain System", which uses AI to manage traffic, parking, and public transport, improving efficiency and reducing congestion [11].
- Bangalore uses AI to monitor traffic and provide real-time information to drivers, helping them choose alternative routes and avoid the most congested areas [12].
- Regione Piemonte, one of the twenty administrative regions of Italy, located in the north–west, has recently reviewed its Air Quality Plan. It has a program to use AI in cities to manage traffic lights, improve traffic fluidity, and reduce emissions [13]. Section 4.2 will be devoted to this particular case study.

The core of the SURTRAC system used in Pittsburgh is its real-time adaptive traffic signal control. The system employs a combination of cameras and radar sensors at intersections to monitor vehicle and pedestrian traffic. These data are fed into an AI algorithm that predicts traffic patterns and adjusts signal timings accordingly. The algorithm optimizes the flow of traffic by reducing stop times, minimizing delays, and preventing congestion from building up. One of SURTRAC's key features is its scalability. The system can be easily expanded to cover additional intersections and adapt to changing traffic patterns. This scalability makes it a versatile solution for both small neighborhoods and large urban areas.

The case of Los Angeles is particularly interesting. Los Angeles, one of the most congested cities in the world, has implemented an artificial intelligence-based traffic management system called Automated Traffic Surveillance and Control (ATSAC). This system uses a network of cameras, sensors, and artificial intelligence algorithms to monitor traffic flow in real time and dynamically adjust traffic signal timings at over 4500 intersections. ATSAC collects traffic data from various sources, including cameras, vehicle detection sensors, and GPS data from smartphones and connected vehicles [6]. Then, AI processes the collected data to assess real-time traffic conditions, identifying congested areas, accidents, and other events that can affect traffic flow [7]. Based on the data analysis, the AI adjusts traffic signal timings dynamically, prioritizing directions with heavier traffic and reducing waiting times for vehicles in queues [8]. The system coordinates traffic signal timings across a wider network, considering traffic flow between different intersections and optimizing traffic circulation on an urban scale.

The implementation of ATSAC led to the following significant improvements in traffic management in Los Angeles:

- Reduced travel times: average travel times have decreased by 12%, with an estimated time saving of 9.5 million hours per year for motorists.
- Reduced emissions: reduced waiting times and improved traffic flow have led to a decrease in greenhouse gas emissions and other air pollutants.
- Improved road safety: optimizing traffic light timing has helped reduce traffic accidents, particularly those caused by running red lights.
- Optimization of public transport: the ATSAC system can prioritize public transport, improving punctuality and efficiency of service.
- The Smart Mobility 2030 Plan of Singapore aims to enhance mobility through technology and innovation. The key issues include connected vehicles to improve traffic flow and safety, smart parking systems that can help to reduce the time spent searching for parking spaces, and the utilization of AI in road safety for monitoring and analyzing traffic violations and accidents, helping to identify high-risk areas and implement safety measures.

In London, AI technologies are used to improve the efficiency and reliability of public transport; in particular, AI predicts when buses, trains, and other vehicles will need maintenance, reducing downtime and preventing service disruptions, and helps in managing passenger flows in busy stations and on platforms. Real-time data analysis aids Transport for London to organize staff where needed most and manage crowd control efficiently.

In Hangzou, the City Brain system, developed by Alibaba Cloud, utilizes AI to enhance urban management, with a primary focus on traffic control. Key components of the system include: (1) data collection from various sources—including traffic cameras, sensors, and GPS devices; (2) real-time analysis (the algorithms process these data in real-time to monitor traffic conditions, predict congestion, and optimize traffic flow); and (3) centralized control (the system integrates data from different departments, providing a unified platform for managing traffic and other urban services).

AI has significantly improved traffic management in Bangalore through adaptive signal control, real-time monitoring, and predictive analytics, reducing congestion and travel times. Enhanced road safety and environmental benefits have also been achieved. Advanced traffic management centers and optimized public transport routes showcase the successful implementation of AI. Future prospects include autonomous vehicles and smart infrastructure, highlighting the importance of public–private collaboration.

Big data, IoT, satellite images and data, cloud computing, smartphones, and hybrid models with AI and machine learning (ML) are currently being used also in the air quality management. Many studies have stressed the importance of these technologies in setting policies, monitoring, identifying emission sources, prediction, health assessment, and citizen participation. A comprehensive review can be found in the work [14].

The aim of the present work is to review the approaches and explore the potential of AI in reducing traffic pollution in urban areas, ranging over three main areas: the optimization of traffic lights timing to reduce delays, the use of AI-powered drones to monitor pollution levels in real-time, and the use of fixed AI-based sensors to detect the levels of pollutants in the air with the use of AI models to identify patterns in the collected data and predict air quality in near-real time. Section 4.1 is dedicated to possible problems arising from privacy protection and data security, and Section 4.2 presents the case study of the Piemonte area and of the city of Turin in the north–west of Italy, where the current situation is depicted and possible local future applications of AI are explored. Finally, Section 5 is dedicated to concluding remarks and possible future perspectives of the present research.

2. Materials and Methods

This study reports the state of the art of the potentiality of AI in reducing traffic pollution in urban areas. A review of the publications available on the main research databases has been performed.

In particular, this study conducted research on the following databases: Scopus, IEEE Xplore, Science Direct, and Research Gate. Scopus is a scientific abstract and citation database, launched by the academic publisher Elsevier. ScienceDirect is a searchable web-based bibliographic database, which provides access to more than 4000 academic journals and 30,000 e-books of the Dutch publisher Elsevier as well as of the ones published by several small other academic publishers. IEEE Xplore is a research database consisting of more than 5 million documents published in 300 peer-reviewed journals, more than 1900 global conferences, more than 11,000 technical standards, almost 5000 e-books, and over 500 online courses on computer science, electrical engineering and electronics, and allied fields. Approximately 20,000 new documents are added each month. It contains material published mainly by the Institute of Electrical and Electronics Engineers (IEEE), but also other publishers' material. Research Gate is a European commercial social networking site for scientists and researchers to share papers, ask and answer questions, and find collaborators.

The used keywords were as follows: traffic lights, air quality, AI for Section 3.1; drones, AI, air quality for Section 3.2; sensors, AI, and air quality for Section 3.3; and privacy, data security, and AI for Section 4.1. Among the results obtained, 148 papers, conference proceedings, and book chapters have been considered and examined, but only 69 have finally proved to be useful for the present research. When it comes to the criteria of selection, papers describing the different approaches used in the optimization of traffic lights' timing have been considered for Section 3.1, along with the ones focused on increasingly larger traffic networks. For Section 3.2, particular attention was paid to papers describing the main advantages and problems arising with the use of drones, together with their use with AI. Basically, the same criteria have been used for Section 3.3, whereas Section 4.1 has seen the selection of paper describing the main solutions developed to protect data security and people's privacy.

In Section 4.2, dedicated to the case study of Piemonte, traffic data provided by 5T, which is an in-house company operating on behalf of the City of Turin, Regione Piemonte, and the Metropolitan City of Turin, managing mobility systems and services (https://www.5t.torino.it/, URL accessed on 13 October 2024), has been processed. These data represent the average speeds of vehicles in several road sections of Regione Piemonte in 2022. They also provide the vehicles' speed in free flow conditions. It was then possible to calculate the ratio between average speed and speed in free flow conditions for each road section and represent it with a color scale in the figures reported in Section 4.2. The open source software Q-Gis, version 3.34.6-Prizren, has been used to process the data, and the results have been represented using the software Arc-GIS Earth, version 2.0.0.3810, released by ESRI on 2 July 2023.

3. Results

As already stated before, the aim of the present work is to explore the potentiality of AI in reducing pollution in urban areas, ranging over three main areas: Section 3.1 is devoted to the optimization of traffic lights timing to reduce delays; Section 3.2 investigates the use of AI-powered drones to monitor pollution levels in real-time, enabling authorities to detect and respond to incidents quickly, preventing critical episodes for air quality; and Section 3.3 deals with the use of fixed AI-based sensors to detect the levels of pollutants in the air and the use of AI models to identify patterns in the collected data and predict air quality in near-real time.

3.1. Optimization of Traffic Light Timing Using AI

Even if exposure assessments focusing on traffic intersections (TI) are still limited, some recent works have demonstrated that signalized TI are pollution hotspots. Particularly, it has been shown that median PM_{10}, $PM_{2.5}$, and PM_1 during delays at TI are 40, 16, and 17% higher compared with free flow conditions [15], and higher concentrations of PM_{10}, $PM_{2.5}$, and PM_1 have been observed at TI with respect to street canyons, parks, and indoor ambients [16]. Other studies have focused on NOx, showing that peak concentrations around signalized TI are five times higher than the quasi-cruising conditions, with 200–1000 extra ppb of NOx at the center of the intersection [17]. It has also been shown the importance of reducing PM pollution at urban TI for health protection purposes [18], and it has been estimated that extreme congestions can cause 20,000 additional deaths due to $PM_{2.5}$ and 5000 due to O_3 in China [19].

A traffic light works by assigning right-of-way to one traffic lane (or many non-conflicting traffic lanes) at a time. The right of way is assigned by turning on a green light for a certain time interval and ends by turning on a yellow light, which starts a change interval, followed by a red light. The typical parameters of traffic light control are cycle, split, and offset [20]. Cycle is the total time of signal indication of green, yellow, and red lights. Split is the sum of green and yellow lights' times. Offset is the delay between the green light starting time in two traffic lights at the same intersection. Usually, cycle, split, and offset follow a daily routine, which is fixed for every traffic light, eventually changing their duration during daytime to face rush hours, but always according to the same previously established cycle. This solution is simple and economic because it allows to avoid traffic detection, but it causes an increment of delay and emissions [21]. Other possible strategies are traffic responsive strategies, isolated-intersection strategies, and coordinated intersection strategies (for a detailed review, see [9]). It has been demonstrated that pollutants' concentrations are significantly influenced by the signal control pattern [22] and that the intervention on traffic lights' time cycle causes NOx emissions reduction [23].

In order to reduce delays at TI and perceive a smoother traffic flow, causing a consequent reduction in pollution, various approaches based on AI algorithms have been used to manage traffic signal timing, usually for coordinated intersection strategies. These include: (1) fuzzy logic [24]; (2) Swarm Intelligence [20,25,26]; and (3) machine learning methods such as Reinforcement Learning [21,27–30].

In [24], a traffic-responsive signal control system is presented, the geometric fuzzy multiagent system (GFMAS), which is based on a geometric type-2 fuzzy inference system. A simulation has been performed over a virtual road network replicating the central business district of Singapore. The results of the simulations show that the GFMAS model performs better than the existing traffic-control algorithms, i.e., green link determining (GLIDE) and hierarchical multiagent system (HMS), obtaining better reductions in traffic and emissions.

Ref. [25] is instead focused on the use of Swarm Intelligence, which is a branch of AI based on the study of the behavior of individuals in various decentralized systems, such as social insect colonies, in which very simple organisms can perform together highly complex tasks by dynamically interacting with each other. In the cited paper, a classification and analysis of the results achieved using Swarm Intelligence to model complex traffic and transportation processes is presented. Among these, a study [31] on traffic light coordination over a traffic network with nine intersections is presented. It is shown that the ant algorithm working on the whole network performs significantly better than the traffic responsive control system of an isolated intersection.

Ref. [27] is a study on a five-intersection traffic network. The work demonstrates the advantage of using a Multi-Agent Reinforcement Learning-based control over a Longest-Queue-First algorithm governing a single intersection. In [29], a Multi-Agent Deep Reinforcement Learning Algorithm called Multi-Agent Advantage Actor Critic (MA2C) is presented. Traffic and emissions simulations were run in two traffic networks located in Bologna (Italy), Andrea Costa (7 signalized intersections acting as agents) and Monte Pasubio (8 signalized intersection action as agents). It has been demonstrated that MA2C produces a reduction in traffic and emissions with respect to non-coordinated networks

The article reported in [30], provides a comprehensive review of machine learning (ML) and deep learning (DL) techniques applied to traffic flow prediction within Intelligent Transportation Systems (ITSs). The core objectives of ITS are to resolve traffic congestion, improve safety, reduce emissions, and enhance overall transportation efficiency. ITS integrates advanced data communication technologies to create a real-time, accurate transportation management system. The paper provides an in-depth analysis of the strengths and limitations of various ML and DL techniques, emphasizing the potential of these technologies to revolutionize traffic management in smart cities.

Google Corporation has recently launched his "Green Light" project (https://sites.research.google/greenlight, URL accessed on 13 October 2024), which uses AI and Google Maps' driving trends to obtain indications to optimize the timing and coordination of traffic lights. The project has been adopted in 12 cities worldwide: Abu Dhabi, Bali, Bangalore, Budapest, Haifa, Hamburg, Hyderabad, Jakarta, Kolkata, Manchester, Rio de Janeiro, and Seattle. The benefits of this method over other approaches have been recently investigated in the case study of Haifa, which is the third city of Israel, with a population of 285,000 inhabitants, 125,000 registered cars, and a road system that includes 162 intersections with traffic lights, serving a metropolitan area of 1,000,000 people [32]. In this study, the authors report their studies on the traffic variability in Haifa and propose a simple method to measure it, based on traffic volumes and delays, on a city-wide scale. Particularly, they used aggregated and anonymized datasets, computed processing unidentifiable trajectories from navigation applications, so that they do not have to use sensors or cameras.

Then, they show that traffic variability can heavily affect the effectiveness of fixed traffic light plans, and possible solutions to mitigate the impact of variability are presented: (1) increasing the number of plans per day decreases traffic variability; (2) positive effects on traffic can be obtained by identifying in advance main public events; and (3) positive effects can also be obtained by detecting changes in traffic distribution. Initial deployment of the method worldwide is said to have shown a reduction of up to 30% in queueing time and 10% in green-house gas emissions.

The use of AI algorithms to dynamically adjust the traffic signal duration to real-time traffic data in increasingly larger traffic networks is very promising in terms of queues and atmospheric emission reduction. However, many of the aforementioned studies do not take into account the fact that TI in cities also involves pedestrians and bicycles. Therefore, in the optimization of signal control, the needs of pedestrians and non-motorized vehicles should be considered, not only looking at the improvement of traffic efficiencies at intersections but also ensuring pedestrians' and non-motorized vehicles' safety. Moreover, traffic light control optimization is usually considered alone, without taking into account the effect of other strategies, such as parking management, public transport priority, etc. An integrated optimization should be pursued in order to achieve a more comprehensive result. Issues of privacy protection and data security also arise. They are addressed in Section 4.1.

3.2. Use of AI-Powered Drones

It is immediately clear that it is not possible to establish a static air quality monitoring station everywhere. Usually, a network of fixed air quality monitoring stations is used together with one or more mathematical models, with a spatial resolution of some kms.

The aim is not to measure pollutants' concentration on a small spatial and temporal scale. The purpose seems rather to be the integration of both stations and mathematical dispersion models to obtain the representation on a county scale of the daily and annual mean concentrations of the main pollutants.

If a smaller spatial and temporal scale is needed, a network of fixed monitoring stations is not adequate; they are fairly sparse and usually situated at irregular spatial intervals. Moreover, on the very small scale, they are only representative of what is happening at the ground level, and they cannot give an overall indication of air contamination (e.g., when tall buildings are present in small scale areas).

In recent years, a mobile solution has been proposed to overcome these problems: unmanned aerial vehicles (UAVs), if equipped with the necessary sensors, can act as independent air monitoring stations and air emission trackers. Moreover, UAVs offer various benefits, incorporating flexible technologies, such as wireless communication. UAVs have been used to obtain 3D maps of $PM_{2.5}$ concentrations at various altitudes [33], and their use has been investigated as a part of the $PM_{2.5}$ monitoring system [34], also with the use of IoT technology [35]. Both of these technologies provide more advantages if they are used together, integrated into what has been called the "Internet of Drones". Air pollution parameters have also been measured and represented in maps based on coordinates [36]. An interesting and more deep review can be found in [34,37,38].

Recently, the UAV-measured data have been used as inputs for a deep learning (DL) model [37]. In this study, after placing the array of sensors on the drone, it was made to fly over the chosen sites. The collected data have then been transferred to the cloud and pre-processed to remove noise and the missings. After that, they have been fed to a DL-based bidirectional gated recurrent unit (Bi-GRU), which retains contextual information throughout the training process, enhancing it. The results of the model have shown to be very close to the real-time data of the same region and better when compared to other types of AI-based prediction models of air quality, proposing a new perspective for the use of smart drones to monitor air quality and of a DL model to forecast it.

Another recent study has proposed a drone-based air quality monitoring solution for a whole city [39]. The entire urban area of Mersin in Turkey has been divided into subregions, and distinct measurements were conducted in each of them, obtaining high-resolution pollution maps. The drone operated autonomously, eliminating in this way the potential errors associated with manual control. This study has also carried out a comparison between the results obtained by UAV-based measurements and the one obtained by a fixed air quality monitoring station, showing that the average relative errors by using UAVs are approximately 6.2% for $PM_{2.5}$ and 6.6% for PM_{10}.

In recent years, SNPA, the Italian national network of Regional Environmental Protection Agencies, has proposed to use drones for environmental monitoring purposes and is currently preparing technical guidelines to reach its aim [40].

However, some problems still remain to be solved and need further research. The magnetic field of the drone, the sound generated by the rotors, and the sudden changes in weather conditions have some influence on the result of the measurements [37]. When pollutants are found as a mixture, it is not easy to measure each of them separately [41,42]. Safety measures must be followed while using UAVs in cities, owing to the presence of tall buildings, trees, power lines, etc., and restrictions are applied in the use of drones for commercial, research, and private purposes [43,44]. Problems arise also from the sensitivity of the sensors used on UAVs when compared to the ones employed in fixed stations and from the brief duration of the sampling time.

As already mentioned, privacy protection problems also arise in this field. They will be briefly summarized in Section 4.1.

3.3. Use of Fixed AI-Based Sensors to Detect the Levels of Pollutants

Estimating the air quality of a region and issuing a warning based on the air quality value is critical to avoid exposure to hazardous pollutants and thus avoid health issues.

If the intention is to investigate on a small spatial or temporal scale, the existing air quality network is not effective. In this case, it can be supported by UAVs, as already stated in the previous section, but also by diffuse low-cost pollution sensors. The study [45] is devoted to the integration of a network of fixed monitoring stations with distributed fixed and mobile low-cost sensors, whereas [46] provides a 100-meter spatial resolution and 10-hour temporal resolution method to forecast $PM_{2.5}$ concentrations using a network of low-cost sensors in the cities of Denver, Columbus, and Pittsburgh (USA). Predictions with 5-hour temporal resolutions are obtained by a combination of three AI algorithms in [47]. The model proposed by [48] instead offers a 30-meter spatial resolution and 1-day temporal resolution predictions for $PM_{2.5}$.

These technological devices are low-cost, compact, and have a low power demand, so their use is going to change air quality monitoring and partially has already achieved so [49]. It has also been shown that soft sensors can be really fast when compared to traditional instruments [50,51]. However, there are still technological challenges in using low-cost pollution sensors, such as their sensitivity, their operational stability, and the duration of their service life; an overview of the problems arising is presented in [52]. A comprehensive review of the efforts made to overcome these problems is reported in [53]. The study [54] is devoted to presenting a new method for accurately calibrating low-cost NO_2 sensors using neural networks trained to forecast sensor correction coefficients and a reference set of data collected from a high-performance fixed monitoring station in the city of Gdansk, Poland.

Low-cost air quality sensors can be used in combination with traffic detectors to observe correlation between traffic and air quality; an example can be found in the work by [55], which uses an automated ML modeling framework and human mobility big data. As stated by the authors of the cited work, the output of these models can help public health officials and policymakers to propose solutions in areas with high $PM_{2.5}$ concentrations (i.e., promote green spaces or reduce emissions from major transportation hubs), identify areas where vulnerable people may be exposed to air pollution, and support evidence-based decision-making. In the aforementioned work [53], the authors established a low-cost network of air quality and traffic sensors at three intersections in the city center of Bielsko-Biała (Poland), measuring PM_1/PM_{10} and $PM_{2.5}/PM_{10}$ hourly averages for almost a month. They found that the traffic contribution to $PM_{2.5}$ was between 6 and 27% and that the worst air quality classes were often recorded after the afternoon commute peak.

Low-cost sensors can also be used, along with forecasting models, to manage traffic and develop a strategy to prevent congestion. In particular, the concentration measured by diffused soft sensors can be modeled to predict future values with various statistical methods. A comprehensive review of the methods used from now on can be found in [3], which proposes also to use neural networks to obtain a non-linear statistical modeling of $PM_{2.5}$ concentrations. They propose to use a Bayesian Regularized Neural Network (BRNN) via Forward Feature Selection (FFS) to forecast $PM_{2.5}$ concentrations in Zuoying district, which is one of the most polluted areas in Taiwan. They found a good correlation, with R-squared around 0.95, and finally propose an air quality warning system, which is very similar to Regione Piemonte's "Air Quality Traffic Light" (see Section 4.2). Other works have shown that better results in the forecast of pollutants' concentrations can be found using an artificial neural network with respect to a linear regression model [56].

The use of low-cost sensors together with AI-driven digital solutions is spreading also in developing countries, where often a network of fixed monitoring stations is not present. In a recent work [57], the AirQo research project (https://airqo.africa, URL accessed on 13 October 2024) is presented, which is a social impact research project started in 2015 at Makerere University, Kampala, Uganda. The project is focused on IoT, data, and AI technologies to support African cities in establishing sustainable and low-cost data systems for tracking and managing air quality. AirQo offers digital solutions, including custom-designed low-cost air quality monitors based on IoT technology, a methodology for deploying a high-resolution air quality monitoring network, AI-powered digital tools for air quality monitoring, and other services that aim to involve citizens and decision-makers in the process.

4. Discussion

4.1. Privacy and Security Questions to Be Solved

On 19 July 2024 the Italian Data Protection Authority opened an investigation into the use of artificial intelligence in the management of traffic lights in the city of Turin to verify the presence of citizens' privacy violations with reference to the current EU laws see [58–60]).

This recent fact sheds some light on one of the two main problems arising from the use of AI technologies, i.e., people's privacy protection and data security of the whole system. Some works have shown that AI-based systems can be subject to external attackers, which can exploit security vulnerabilities for information theft to take control of the system or perform Distributed Denial of Service attacks [61,62].

Machine learning models are trained on raw data that contain sensitive information, and data sharing can lead to information leakage. Many different works propose the use of Federated Learning (FL) to avoid these problems because FL users locally train models and only the trained model parameters are transmitted to the remote servers without disclosing private datasets (e.g., [63–65]). In fact, FL is a machine learning setting where many users (or clients, e.g., mobile phones, sensors, etc.) train together a model under the direction of a central server (e.g., server provider) while maintaining the data training process [66]. An example of a FL-based computing scheme for the use of drones to monitor urban transportation can be found in [67].

However, neither FL is immune to external attacks. The problem of securely transmitting model parameters without disclosing private datasets is known as secure aggregation, and the proposed solutions still suffer in the case of complex networks. The study [68] proposes to use a particular version of differential privacy, which employs cryptographic techniques in combination with randomization procedures in the transmission of data from the user to the aggregator [69,70]. This way of using differential privacy offers an efficient way to deal with the problem, but it must be underlined that it remains a challenge to maintain an appropriate trade-off between privacy and model quality in DL models.

4.2. A Case Study: The Piemonte Area in the North–West of Italy

Ref. [71] has established that Member States of the European Union (EU) shall assess ambient air quality in all their zones and agglomerations, and that in all zones and agglomerations where the level of pollutants exceeds the upper assessment threshold, fixed measurement stations shall be used to assess the ambient air quality, eventually supplemented by modeling techniques and/or indicative measurements to provide adequate information on the spatial distribution of the ambient air quality. "Zone" means part of the territory of a Member State, as delimited by that Member State for the purposes of air quality assessment and management, whereas "agglomeration" means a zone that is a conurbation with a population of more than 250,000 inhabitants or, where the population is 250,000 inhabitants or less, with a given population density per square km.

It is immediately clear that it is not possible to establish a static monitoring station everywhere. With regard to the already mentioned Regione Piemonte, a comprehensive system of 58 stations has been established in a territory that is 25,387.07 square kilometers wide (see Figure 1 and ref. [72]). Moreover, the mathematical models in use have a spatial resolution of 4 km. The aim of the Directive is not to measure pollutants' concentration on a small spatial and temporal scale, which cannot be obtained by a network of stationary air quality monitoring stations. The purpose seems rather to be the integration of both stations and mathematical dispersion models to obtain the representation on a county scale of the daily and annual mean concentrations of the main pollutants.

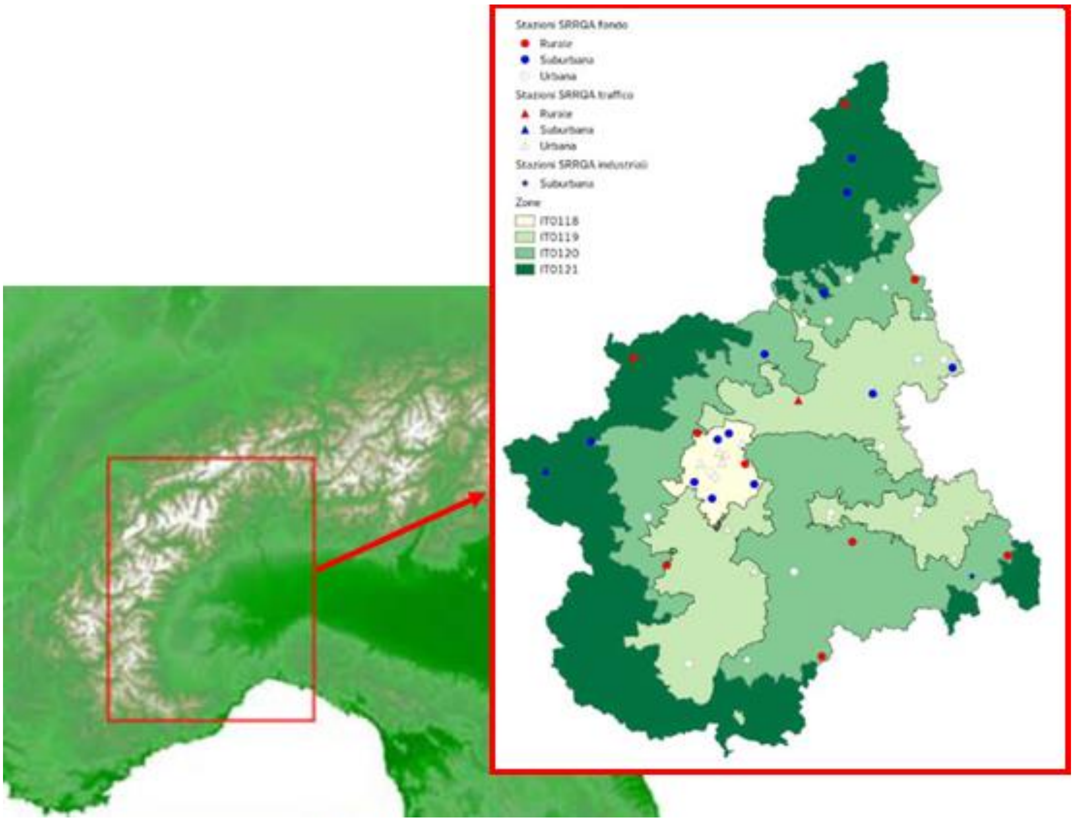

Figure 1. Regione Piemonte, in the north–west of Italy, with zones and the agglomerate of Turin (in white). Triangles and circles identify the fixed air quality monitoring stations. Authors' elaboration from Regione Piemonte Air Quality Plan 2019 (see [72]).

In the northern part of Italy, the Po valley suffers from one of the worst air qualities in Europe, due to high anthropogenic emissions in combination with frequently occurring stagnant atmospheric conditions [73–75], as one can notice in Figure 2.

Figure 2. Stagnation of aerosols and suspended particles over Piedmont on a clear day at the end of November 2014 (from [72]).

Following an agreement between the Italian Regions of the Po valley, Regione Piemonte has decided to introduce the possibility of activating temporary measures in the period between 15 September and 15 April. The measures are activated when the air quality forecasts, formulated by ARPA Piemonte—the Regional Environmental Protection Agency—on the basis of integrated meteorological and air quality evaluation and forecasting modeling systems, indicate the exceeding of the daily limit value of PM_{10} for three consecutive days, i.e., the control day and the two following days. The air quality forecasts are represented as a traffic light, with red light meaning the forecast of three consecutive days above the value of 75 $\mu g/m^3$ of PM_{10}, orange representing the forecast of three consecutive days above the value of 50 $\mu g/m^3$ of PM_{10} (the daily limit value imposed by the EU), and green light meaning no troubles. The temporary measures to be adopted concern mobility, heating, and agriculture and consist of limitations to vehicular traffic, bans on burning plant material and any open combustion, limitations on the distribution of fertilizers and animal manure spreading, and limitations regarding fuels and heat generators for domestic heating [76].

The "Air Quality Traffic Light", which is the forecast coming from the integrated air quality evaluation and modeling system, is devoted to a county scale, having a spatial resolution of 4 km and daily average concentration values (i.e., temporal resolution of 1 day). It plays a role that is very similar to the air quality warning system proposed by [50], based on BRNN-FFS, even if on completely different bases.

Traffic plays a central role in the bad air quality levels measured in Piemonte, especially in winter time. In Figure 3, a particular of the city center of Turin, with 850,000 inhabitants in the north–west of Italy, can be seen. Each road segment has been colored in red if the average speed in 2022 was less than 50% of the speed in free flow conditions, in orange if it was between 50 and 75%, in yellow if it was found among 75 and 95%, and in green if it was more than 95% (data provided by 5T). Even if they are yearly averages, lowering the peaks of traffic congestion in rush hours, there are still many red and orange segments, highlighting the traffic problems of the city.

Figure 3. Ratio between average annual speed and speed in free flow conditions in the city of Turin, north–west of Italy (2022 data).

In future work, the authors aim at extending the analysis of annual traffic data in the City of Turin, provided by 5T, to different years and to make a comparison between the average annual speed/speed in free flow conditions ratio and the annual mean concentrations of $PM_{2.5}$, PM_{10}, and NO_X measured by the fixed air quality monitoring stations located near TI to obtain local confirmation that pollution at TI is strictly connected to traffic delays. In Figure 4, an example can be seen of a TI of interest, located near the air quality monitoring station called "Torino—Grassi".

Figure 4. TI in the city of Turin, located near the fixed air quality monitoring station "Torino—Grassi" (the checkered circle), to be the object of future research on the correlation between traffic conditions and air quality near TI.

Regione Piemonte, with an official act [77], has recently adopted a new Regional Air Quality Plan, with a full new set of action and measures to achieve its strict air quality targets (see "Annex A—Actions and Measures" to the plan, [13]). Following the examples cited in the Introduction Section, one of the proposed actions is devoted to the use of AI to manage the whole traffic lights system of a city to obtain smoother traffic and a reduction in pollutants' emissions. Regione Piemonte aims to experiment it in Turin, the most important and populous city of the north–west of Italy and the 4th by population of the whole country, with approximately 850,000 inhabitants, and then to extend it to all the cities with more than 30,000 inhabitants. The application of this measure is expected to reduce emissions of NOx by approximately 297 t/a, PM_{10} by 61.3 t/a, and $PM_{2.5}$ by approximately 24.5 t/a.

The authors aim at following the application of AI technologies to manage the whole traffic lights system of Turin and to verify, as far as possible, the expected reduction in pollutant emissions.

5. Conclusions

In this study the potential of AI to reduce pollution in urban areas has been explored, through a review of the current scientific literature, ranging over the following three areas: the optimization of traffic lights timing to reduce delays (Section 3.1); the use of AI-powered drones to monitor pollution levels on a small time and dimensional scale, enabling authorities to detect and respond to incidents quickly, preventing critical episodes for air quality (Section 3.2); and the use of fixed AI-based sensors to detect pollutants' levels in the air on a small time and dimensional scale and the use of AI models to identify patterns in the collected data and predict air quality in near-real time (Section 3.3).

The use of AI to optimize traffic light timing and coordination in increasingly larger traffic networks has proven to be very promising. Several works have demonstrated that coordinated traffic lights obtain better results with respect to the optimization of a single traffic light and that an optimized time cycle performs better than a fixed plan in terms of queues and emission reduction. The research in this area seems to move in the direction of a dynamical adaptation of traffic light timing on a city-wide scale, based on real-time traffic data, both given by fixed sensors or by aggregated and anonymized datasets, computed processing unidentifiable trajectories from navigation applications. Some questions remain to be solved because the needs and safety of pedestrians and non-motorized vehicles are usually not considered, and traffic light control optimization is usually considered alone, without taking into account the effect of other strategies, such as parking management, public transport priority, etc.

When it comes to the use of drones, they have proven to be very useful on a small spatial and temporal scale, where a network of fixed monitoring stations is not adequate. UAVs, if equipped with the necessary sensors, can act as independent air monitoring stations and air emission trackers. Recently, the UAV measured data have been used as inputs for a DL model, whose results have shown to be very close to the real-time data of the same region and better when compared to other types of AI-based prediction models of air quality, proposing a new perspective for the use of smart drones to monitor air quality and of a DL model to forecast it. However, the following problems need further research: (1) the magnetic field of the drone, the sound generated by the rotors and the sudden changes in weather conditions have some influence on the result of the measurements; (2) when pollutants are found as a mixture, it is not easy to measure each of them separately; (3) safety measures must be followed while using UAVs in cities, owing to the presence of tall buildings, trees, power lines, etc., and restrictions are applied in the use of drone for commercial, research and private purposes; and (4) problems arise also from sensitivity of the used sensors when compared to the ones employed in fixed stations and from the brief duration of the sampling time.

If the intention is to investigate on a smaller spatial or temporal scale, the existing air quality network can also be supported by diffuse low-cost pollution sensors, which can provide a method to measure (and the forecast, together with AI algorithms) pollutants' concentrations at a spatial resolution up to 30–100 m and a temporal resolution up to 5–10 h. These technological devices are low-cost, compact, and have a low power demand, so their use is going to change air quality monitoring and partially has already achieved so. However, there are still technological challenges in using low-cost pollution sensors, such as their sensitivity, their operational stability, and the duration of their service life.

Problems of privacy protection and data security arise from all three areas. Some works have shown that AI-based systems can be subject to external attackers, which can exploit security vulnerabilities for information theft to take control of the system or perform Distributed Denial of Service attacks. Many different studies propose using FL to avoid these problems because FL users locally train models and only the trained model parameters are transmitted to the remote servers without disclosing private datasets. Some authors have also proposed using a particular version of differential privacy, which employs cryptographic techniques in combination with randomization procedures in the transmission of data from the user to the aggregator. This way to use differential privacy offers an efficient way to deal with the problem, but it must be underlined that it remains a challenge to maintain an appropriate trade-off between privacy and model quality in DL tasks.

Author Contributions: Conceptualization, A.R., L.M., E.B., E.R. and C.B.; methodology, E.B. and C.B.; validation, A.R., E.B. and L.M.; formal analysis, E.B. and C.B.; investigation, E.R.; resources, E.B. and E.R.; data curation, E.R.; writing—original draft preparation, C.B. and E.R.; writing—review and editing, E.B.; supervision, A.R., L.M. and C.B.; project administration, C.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Traffic data used in Section 4.2 are property of 5T. In case of interest they should be requested to the owner.

Use of Artificial Intelligence: AI or AI-assisted tools were not used in drafting any aspect of this manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

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