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Original Article

The Role of Machine Learning in Vehicle Emissions Reduction

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Abstract *The transportation of people and goods presents a long-standing conundrum for public policymakers. This is amply demonstrated in the transportation sector among the greenhouse gas (GHG) emitters: it represents 17.9% of global anthropogenic GHG emissions (up to 24% when accounting for indirect emissions) and 23% of the energy-related CO2 emissions, with annual increases of GHG emissions of more than 3% in the last 35 years. It is difficult to deny that transport has provided a level of economic development that is beneficial for people worldwide. However, the sector contributes to air quality and noise pollution. There is also a large social cost due to road accidents. Furthermore, the combined effects of urbanization, globalization, and technological progress are creating further challenges, such as congestion and lack of accessibility. To manage these sustainability trade-offs, public policy has made use of a combination of technological, regulatory, behavioral, and economic measures. One of the solutions proposed by experts for the expansion of the environmental vehicles stock rate is the use of zero-emission vehicle (ZEV) synthetic fuels. ZEV synthetic fuels act as an enabler of mass penetration of the environmental vehicle stock by catering to usage patterns and transit types that are unattractive to electric vehicles (EV), such as heavy-duty, aviation, and shipping. These fuels are produced in periodic bioenergy using biomass or synthesized from renewable sources such as carbon dioxide, water, and electricity. The electricity can come from renewable sources, including hydroelectric, wind, and photovoltaic power, as well as from secondary sources such as nuclear power and fossil fuels with carbon capture and storage, using electrolysis to produce hydrogen and the application of chemical processes to create synthetic fuels using the aforementioned hydrogen and captured carbon dioxide as feedstock.*

Keywords: *Machine Learning in Vehicle Emissions Reduction, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM), Computer Science, Data Science, Vehicle, Vehicle Reliability.*

I. INTRODUCTION

In prior work exploring the potential for machine learning (ML) to augment exhaust emissions-related research, we observed that while approaches using machine learning were starting to be applied, broader capabilities that ML, when incorporated into a larger computational model, could drive a transformation of how research is conducted. In particular, we speculated that ML could help us more effectively turn the ever-increasing quantity of collected data into information and, ultimately, knowledge about emissions-related environmental and public health issues. We proffered that emerging developments in ML open up exciting possibilities for enabling a shift from a deeply data-starved, hypothesis-driven paradigm toward a richer, big-data-infused, competence-driven paradigm; here, framework and models trained not on isolated observations, but rather on consolidated, diverse, and curated data from other, conceptually- or physically-related domains.In this perspective piece, I will revisit these observations in the light of the 4 years that have since passed, and we will lay out a high-level aspirational vision for the community to embrace. After a brief examination of supporting trends and milestones, I will first propose a systems-wise perspective for progress that emphasizes thinking about machine learning in vehicle emissions research in the context of a broad societal challenge and then will elaborate on desiderata for future research, including a set of scientific domains that provide promising sources of inspiration for immediate action.

II. BACKGROUND AND MOTIVATION

Global emissions of carbon dioxide, associated with human activities, have increased at an average rate of 0.8% per year from 2009 through 2018. In 2018, total global CO2 emissions from fossil fuel and cement production were 37.1 GtCO2. This high level of emissions contributes to rapid climate change due to the well-mixed nature of CO2 in the atmosphere. In 2018, approximately 9.7% of the CO2 was produced by vehicles. On-road vehicles remain the major contributor to growth in global oil consumption, and the majority of their emissions are produced on the urban scale. As shown in Fig. 1.1, air pollution leads to significant adverse impacts on human health. Several highly cited studies have found that air pollution and associated impacts lead to a wide range of health outcomes, e.g. higher mortality risk, an increased incidence of asthma crisis, and, over the long term, increases in chronic diseases (e.g., respiratory diseases, cardiovascular disease, and cancer). Since the intended mode of transportation in large urban areas will remain automobiles for the near future, there is a critical need to reduce vehicle emissions while still enabling individual mobility.

III. RESEARCH AIM AND OBJECTIVES

The paper sets out to review and evaluate the literature on emissions-reducing the role of machine learning in the vehicle domain. The authors conduct a thorough review and analysis of trending and state-of-the-art applications of machine learning for vehicle emission mitigation, aiming to guide further development and use of relevant machine learning-based methods and tools. A set of essential research questions and a detailed list of crucial learning objectives and study objectives are accordingly identified. To make the most of machine learning techniques for vehicle emissions reduction, researchers need to focus on high-added-value applications, which pave the way for a supportive policy. Learning outcomes from the post-COVID-19 semi-urban environment and mobility context are also expected to emerge and orientate the societal transformation toward carbon footprint reduction.

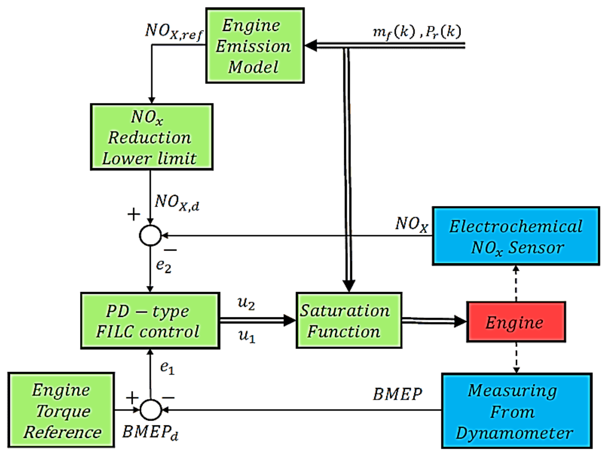

Figure 1: Block Diagram of Emission Control Strategy

A. Understanding Vehicle Emissions

Vehicle emissions are gasses emitted by motor vehicles that produce adverse environmental effects, air pollution, or deadly toxins. These emissions can be divided into three categories: regulated emissions such as particulate matter, unregulated emissions, and greenhouse gasses. Regulated and unregulated emissions poison the environment and humans, as well as contribute to global warming. Different regulatory standards are in place globally to limit and control these emissions. Abiding by these standards is critical to air quality and human health, and the numerous technologies used to reduce vehicle emissions contribute to technology industry growth.Currently, several different methods to measure gaseous emissions are available. The most commonly used method is used to measure engine performance, and emissions are measured from a few short driving cycles. These tests are expensive, and as a consequence, they are conducted on limited vehicles manufactured for evaluation. The recent diesel emission scandal revealed that the emissions generated by those vehicles under regular driving cycles were significantly higher compared to measurements made in labs. This experience emphasizes the need for cheap, reliable, and on-road measurement gear.Nonetheless, CO_2 emissions are measured both during testing and real driving cycles using standardized procedures. Due to recent advances in vehicle technologies, the gap between test and certification vehicle performance emissions is widening. Commercial, light-duty vehicles are highly instrumental in reducing CO_2 and GHG emissions. The International Energy Agency estimated how critical these vehicles were to improving the transport industry for environmental sustainability, particularly for international freight.

B. Sources of Vehicle Emissions

There is a range of exhaust and non-exhaust vehicle emissions. Exhaust emissions are a result of the combustion process and can be divided into regulated (measured as part of standardized test cycles) and unregulated compounds. Regulated emissions include carbon monoxide (CO), nitrogen oxides (NOx), hydrocarbons (HC), and particulate matter (PM). Unregulated emissions, also called toxic gasses, are currently not measured or regulated, despite having a detrimental effect on air quality and human health, and include aldehydes, nitriles, amines, sulfurs, mercaptans, and heavy metals. Furthermore, exhaust emissions include GHGs, whose regulation is intrinsically tied to fuel combustion and consumption. Non-exhaust vehicle emissions are those that arise from wear processes (brake, tire, road dust) and re-suspension. These are mainly composed of minerals and metals and might include particles of smaller sizes than traffic-related particulate matter.Table 1 summarizes the pollutants (both particulate and gaseous) along with the potential methods of measurement, the parameters or properties they rely upon, and the principal sources from where these pollutants are emitted. The emissions occur both during the vehicle operation (cold start, high load, steep gradients) and during resting (especially evaporative losses). The emissions vary according to diverse variables (e.g., vehicle parameters, traffic conditions, climatic, road conditions, geographical, etc.) and have a characteristic dependence on fuel, engine type, configuration, capacity, and age, fuel adaptive calibration, after treatment, and recovery devices. The complex dynamics of vehicle emissions (from pollutants formation in the combustion process to the fate in ambient air, physical and chemical transformations and stochastic nature of atmospheric conditions and chemical and physical processes, the inclusion of the chemical mechanisms in atmospheric models) make them unique, thus entailing the need for approaches tailored to their reduction.

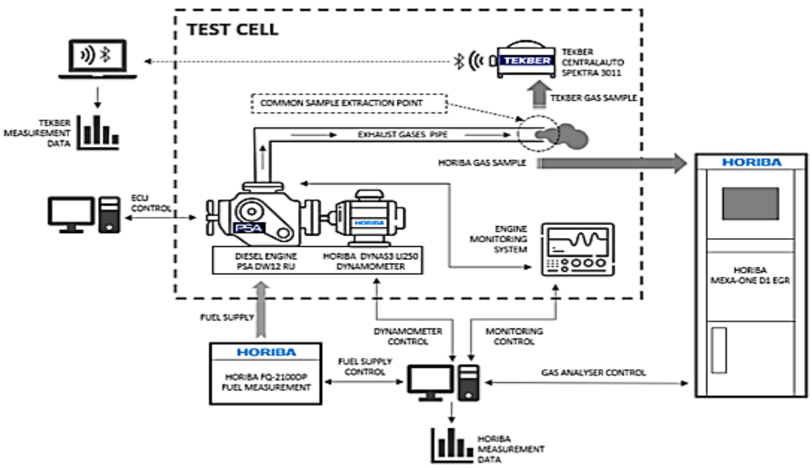

Figure 2: Test Cell Schema with Tekbar and Horiba Gas Analyser Installation

C. Impact of Vehicle Emissions

Numerous factors impact the scope to which passenger and commercial vehicles contribute to air pollutants globally. Over the past several decades, air quality has been generally improving in the U.S. due to control measures including vehicle emissions standards, reductions in sulfur levels in gasoline, straightforward technologies to control nitrogen oxides (e.g., selective catalytic reduction), and computerized and heterogeneous cleanup of other air pollution sources. Despite these improvements, vehicle emissions continue to be a significant problem on a regional and local basis, especially in areas around ports or highways, with varying levels of air quality across U.S. states and regions. On-road vehicles are estimated to account for over 45% of anthropogenic emissions of NOx and over 75% of CO emissions in nonattainment areas. In CA, the largest source of NOx emissions is from vehicles in the SFB region, primarily heavy-duty trucks.

Heavy-duty trucks also greatly contribute to diesel PM and black carbon emissions. National estimates show heavy-duty vehicles as accounting for about 31% of GHGs and 25% of total U.S. energy consumption. Heavy-duty vehicles are estimated to be responsible for producing approximately 77% of the total PM10 emissions and 85% of all total PM2.5 emissions from the transportation sector. Recently identified as carcinogens, new studies are documenting diesel PM emissions to have numerous negative public health effects, both locally and regionally, and effects persist even if the air is within today's stringent U.S. Environmental Protection Agency (EPA) standards.

The evidence warrants taking aggressive action to control these emissions. Regulatory agencies are focused on heavy-duty vehicles for addressing the diesel PM and black carbon emissions as it is clear that increasing use of natural gas or other cleaner alternative fuel technologies has been slow to manifest in the sector. Furthermore, during this transition period of electrification of the transportation sector, an anticipated further room in regulatory control is needed as emissions are predicted to increase with the rise of the economy. Robust scientific studies of the on-road heavy-duty truck fleet are needed to evaluate policy options posed by emerging technologies since there is substantial diversity in the characteristics of the different groups of heavy-duty trucks.

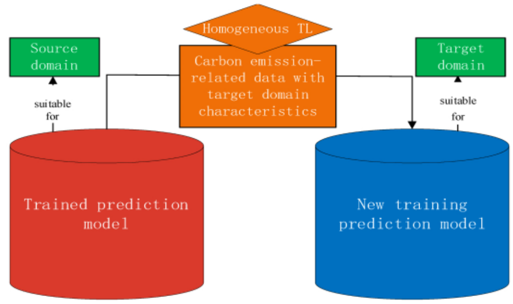

Figure 3: Transfer Learning Process of Prediction Model-Own Elaboration

D. Machine Learning Applications In Emissions Reduction

A plethora of scientific work has explored the topic of vehicle emissions reduction across a wide range of methods and strategies. A review summarizing some of this work was recently published. However, the growing interest in machine learning methods, along with their increasing prominence in emissions reduction research and the publication of the latest research applying machine learning to various vehicle emissions reduction-related topics, has led to a noted recent increase in the number of scientific articles covering the same. It is increasingly common to find papers that explore the application of machine learning in vehicle emissions reduction topics, including fuel economy improvement, driving behavior inference, after-treatment system control, emissions monitoring, emissions prediction, emissions impact or social cost prediction, vehicle health management, emissions-independent vehicle factor identification, and emissions testing among others. Indeed, it is clear that machine learning has a role to play across a wide spectrum of vehicle emissions reduction-related topics and will find truly varied applications in the coming future.

Providing an outline of the growing mass of machine learning methods in the ordered structure of a review aims to assist those interested in applying these methods in vehicle emissions reduction by enabling the potential researcher to identify the most appropriate references and methods, by providing an introductory reference to machine learning methods for those new to the subject, and by identifying gaps in the application of machine learning techniques to problems in vehicle emissions reduction that warrant further study. The review is structured to provide an exposition of the types of machine learning algorithms that have found use so far in vehicle emissions-related studies, the way that these methods are applied, which vehicle types or elements or emissions have been addressed by these algorithms, what sort of data handling methods these studies are employing, relevant decision support aspects, and finally, the limitations and challenges of using machine learning methods in vehicle emissions reduction.

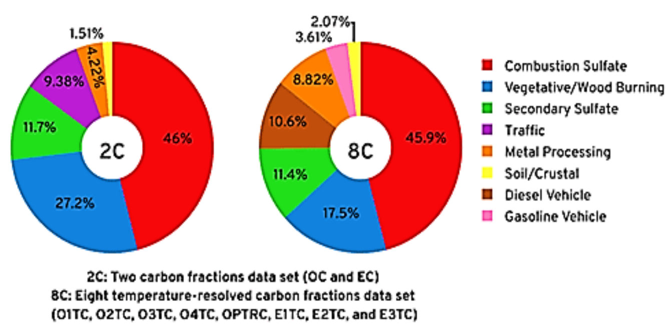

Figure 4: Source Contributions Obtained Using SC for 2C and 8C Data Set

E. Data Collection And Analysis:

An automotive vehicle collects data that feeds its control and infotainment systems. Data collected by these systems make it possible to perform multiple machine learning tasks and improve emissions reduction at the vehicle and the road network level. At the vehicle level, fuel consumption or acceleration patterns can be retrieved from the vehicle bus to assist eco-driving applications. Specific types of data are also used to monitor the status of the catalytic converter. Automated vehicle homologation based on actual driving data contributes to the availability and transparency of emissions-reduction technologies in the whole population of vehicles. At the road network level, speed profiles can be analyzed to improve traffic emissions estimation. Sensor data can be provided also by Wireless Sensor Networks installed along road infrastructure. Nowadays, intermittent and static sensors deployed on road infrastructure and fleet of vehicles are connected by the Internet of Things facilitating the acquisition and transfer of data from several heterogeneous sources. At the intersection between smart cities and transportation, data generated by a diverse set of sensors are collected at the edge of the network and carried over multi-access mesh networks to the cloud, where it is further processed for many applications. Data can be transmitted over many different technologies and solutions. The most common protocols and communication standards are enumerated and compared. For static sensors, typical protocols are CoAP, MQTT, FTP, HTTP, and REST; for vehicles, it is Car2Car communication using DSRC for safety applications and LTE for after-market and cloud-based services. 5G communication is a new promising approach that can ensure the exchange of a massive number of sensor data while maintaining low latency. The high availability and good quality of these types of data, however, are still a challenge in many applications and operational contexts. Study cases are also part of the problem, involving limited periods and areas of investigation. Data almost always come from isolated, un-peer vehicles, while road transport simulations at different dimensions require broader and heterogeneous databases. Such characteristics make data usually unsuitable for application with artificial intelligence, and in particular machine learning techniques. Despite that, many researchers and IoT developers are attracted to the innovation and business opportunities associated with IoT technologies for wireless communication, data analytics, and cloud storage services, and focus on the typical machine learning workflow for IoT applications, which are crafted revisions of standard approaches.

F. Predictive Maintenance and Optimization

As noted, predictive maintenance and associated optimization of vehicle/fleet downtime are essential tasks. Should a preventive approach, in service time suffice, a vehicle should be taken out of service. Predicting with accuracy the time of occurrence of a part could be applied to repair and maintenance systems in which car parts are replaced or repaired before they break, known as "Predictive Maintenance" (PdM), and to logistics problems concerning vehicle downtime (VDT). Once a part-specific algorithm produces a prediction giving the expected time of occurrence T for part replacement and repair, the number of additional hours worked by the vehicle can provide an accurate estimate of vehicle downtime. The speed of the DMS system schedules the vehicles so that the additional work, vehicle travel times, and vehicle maintenance times are minimized. The vehicle downtime objective function translates into other objectives particularly important for economical vehicle repair planning. These might require reaching a reduced number of vehicle maintenance points nested into PdM, bearing in mind that the cost of vehicle damage increases as the vehicle is operated until the part breaks. These numbers should satisfy upper bounds specifications that result from vehicle transfer time requirements and satisfy vehicle-specific bonuses. Furthermore, we formalize the optimization problem for a set of vehicles going from their different origins to various destinations.

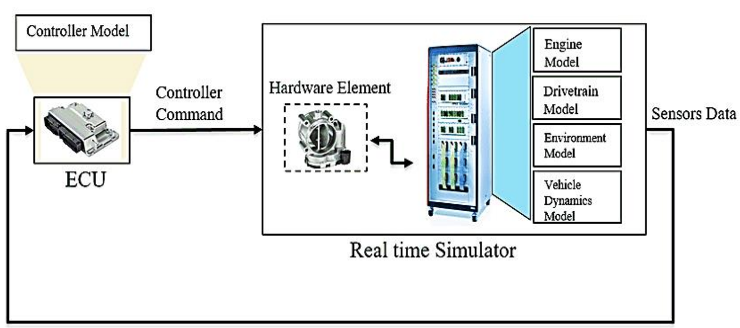

Figure 5: Hil Real - Time Simulation with Real ECU

IV. CASE STUDIES AND SUCCESS STORIES

Case studies and success stories are popular means to convey successful machine learning cases and allow the extraction of critical lessons. In the context of vehicle emissions reduction, vehicle routing, and supply chain management, the integration of advanced data analytics, machine learning, and simulation optimization tools leads to profound changes in logistics and reduces emissions, as documented in key cities such as São Paulo. The implementation of these highly innovative methods typically leads to both economic and environmental improvements, which are translated to the transport of raw materials and finished products in various industries, such as cement, food packaging, and optical lenses. In the context of electric vehicle urban last-mile deliveries, machine learning allows the optimization of driver scheduling to fit electrical vehicle characteristics and energy needs, furthering the development of zero-emission street logistics.

In the fleet management of hybrid delivery services of letters, parcels, and non-palletized goods in city logistics, upon which the future of cities greatly relies, a machine learning-based decision-assistance model shows notable performance. Overcoming the computational limitations of highly accurate safety surround view applications for electric city vehicles is a demonstrable outcome of using cutting-edge deep learning in exploiting the computing power of modern many-core GPUs.Employing scalable time-series deep learning in producing highly accurate estimates of emissions generated by traffic flows in urban areas is a goal to which a demand-responsive approach leveraged on autonomous and high-frequency air pollution measurements from task-dedicated mobile monitoring systems greatly contributes. Federated learning, a branch of distributed machine learning that learns or trains models on edge the user, valuable for fleet management applications reliant on the highly personalized treatment of energy consumption behaviors of drivers. Reduced emissions from energy-efficient speed control and braking systems usage in underground urban transportation are two, even more, tangible outcomes of combining scheduling optimization and statistical modeling with sensor device data acquisition and analysis toward autonomous KPI measurement in tramway driver metro missions.

V. CHALLENGES AND FUTURE DIRECTIONS

Concerning the strengthening of incentives, the co-authors call upon the use of policy-neutral criteria to determine the vehicles that are eligible for receiving a bonus. The scientists suggest that these are either cheaper incentives, such as faster deregistration of dirty vehicles and free access to urban highways, or bonus-malus alterations that are budget-neutral or with 80% budget-neutrality. Another potential strategy is targeting less SUV-like and especially BEV or PHEV designs. Focusing more on non-road sources will also be important. Finally, the scientists suggest more ambitious targets, especially with scenarios that define separate L categories and SUV targets.

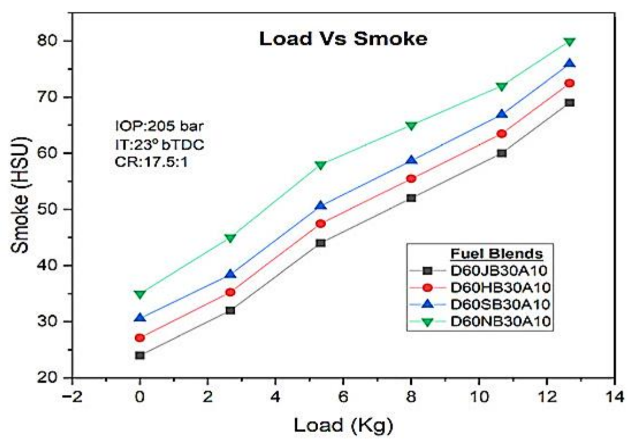

Figure 6: Smoke with Engine load for the developed biodiesel blends

There are several recommendations for the improvement of vehicle emissions reduction efforts. They are offered as a scientific opinion. Politicians, regulators, and experts need to consider and further test some of the options. Even if none of the ideas show promise, the scientists are convinced that the report can still be relevant by specifying what does not work or cannot be realized. The study is important as emissions from Land Transport are responsible for a significant fraction of EU costs related to environmental and health effects from the impact of air pollutant exposures. These problems are more serious now than in the past, especially with the increasing prevalence of inactivity and obesity-related problems. The paper, therefore, lists the priority Themes/Challenges related to Land Transport emission reduction that address these needs.According to the authors, the role of the Member State in the current new Vehicle Type Approval framework should set additional refinement steps for the development of the Member State LRTPs, close the existing data gap in the real-world emission profiles and emissions dispersion models in the Member States, and endorse a duty cycle definition for the Member States for the type-approval test protocol, no longer applicable to the Member State LRTPs, until a new and specific duty cycle is adopted for them. Such an important task can be achieved using LIDAR analysis and mobile vehicle emission laboratory measurements. These tools can be used for source detection and forest emission dispersion acquisition in support of Member State LRTPs, for in-depth knowledge of the real-world profiles, and for vehicle categorization based on the real driving emissions performance. A credible number of data points on the number of travels and total mileage accumulated in urban or suburban travels for the different vehicle impulse response assumptions should be collected. LIDAR and vehicle system signals should be analyzed to detect real-world local response, according to defined duty cycles, maneuver frequencies, and amplitude and edge conditions.

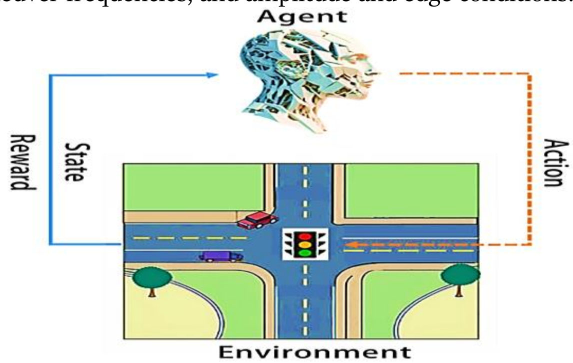

Figure 7: Deep Reinforcement Learning For Traffic Signal Control

VI. CONCLUSION

The widespread use of machine learning in vehicle emissions reduction has increased rapidly over the past years due to breakthroughs in the field. This paper presents an overview of a set of insightful findings from notable researchers working on vehicle emissions reduction and machine learning. The significant progress by the researchers has made the methods and concepts more accessible to both academia and industry and continues to increase future positive impacts. The results for implementing machine learning and non-machine learning-based model simulations vary among studies and the most advanced results show promising reductions in CO_2, CH_4, CO, NO_x, SO_2, hydrocarbons, and greenhouse gasses. This speaks to the need for a more comprehensive and harmonized perspective on emissions controls with a range of user-friendly real-world implementations. In the long term, this knowledge could reduce global emissions and improve the quality of roads in the future. Specific focus should be placed on controlling the use of automated machine learning through automatic models, hyperparameters, and flicker designs for fast vehicle emissions reductions on a local level. This is important for vehicle emissions of cities and for fast urban planning to increase the quality of life and the economic value of the regions of the world concerned.

A. Future Trends

The past three years have seen the growth in the importance of machine learning (ML) within the field of reducing the environmental impact of vehicle emissions. This work champions the need for data, the challenges of model and data interpretability, benchmarking and testbeds, and the importance of motivating deep environmental learning solutions. Drawing on recent practice and research at the Bosch Center for Artificial Intelligence and academic networks, we also present future trends within the roles of ML in vehicle emissions reduction. First, there is a significant need for enhancements in all forms of sensors that can provide the required granularity of chemical concentration information: spatiotemporal and across multiple pollutants. However, given the roadmap to electrification and smart city/mobility visions for a more sustainable future, there will be significant but challenging opportunities to leverage non-environmental monitoring sensors within vehicle platforms to derive environmental learning solutions. City planners and local governments routinely manage city service delivery via energy, traffic, and waste management infrastructures, and dialogue with security and safety sensors. With co-optimization of neural network-friendly sensor designs, fusion architectures, system optimization, and training models and methods, these sensors can yield added societal value, e.g. through more affordable air quality chemo sensation patch deployments and/or other multipurpose sensor deployment

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