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RESEARCH ARTICLE

Internet-of-Vehicles Network for CO_2 Emission Estimation and Reinforcement Learning-Based Emission Reduction

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ABSTRACT The escalating impact of vehicular Carbon Dioxide (CO_2) emissions on air pollution, global warming, and climate change necessitates innovative solutions. This paper proposes a comprehensive Internet-of-Vehicles (IoV) network for real-time CO_2 emissions estimation and reduction. We implemented and tested an on-board device that estimates the vehicle's emissions and transmits the data to the network. The estimated CO_2 emissions values are close to the standard emissions values of petrol and diesel vehicles, accounting for expected discrepancies due to vehicles' age and loading. The network uses the aggregate emissions readings to inform the Reinforcement Learning (RL) algorithm, enabling the prediction of optimal speed limits to minimize vehicular emissions. The results demonstrate that employing the RL algorithm can achieve an average CO_2 emissions reduction of 11 kg/h to 150 kg/h.

INDEX TERMS Emission estimation, CO_2 emissions, Internet-of-Vehicles, emission reduction, reinforcement learning, traffic management.

I. INTRODUCTION

Vehicles are one of the main sources of Carbon dioxide (CO_2) emissions that contribute to air pollution, global warming, and climate change [1], [2]. Many developed countries aim to reduce CO_2 emissions by 50%-55% by 2030-2035 and cut it entirely by 2050 [3], [4]. Considering the necessity of CO_2 emissions reduction, several intelligent transportation systems (ITS) are proposed, including traffic management and control, eco-navigation and monitoring, vehicle dynamic state control, driver assistance, and cooperative communication systems [2], [5]. However, to develop and implement ITS-based emissions reduction systems, a real-time emissions estimation and monitoring system is required [6]. Emission estimation depends on many parameters related to road topology, vehicle characteristics and dynamics, as well as traffic and atmospheric conditions [2]. Hence, to estimate vehicular emission, different emission models were proposed based on collected data about these parameters at microscopic, mesoscopic and macroscopic scales [7].

The related works that discussed models of emission estimation, the use of machine learning algorithms in ITS, and the application of vehicular communications to address emission reduction are discussed in following section.

A. RELATED WORKS

1) MODELS FOR VEHICULAR EMISSION ESTIMATION

Microscopic models require a second-by-second vehicle's trajectory and dynamics data to estimate emissions values accurately. However, microscopic models are highly computational and storage demanding [8]. Examples of microscopic models are MOBILE and Motor Vehicle

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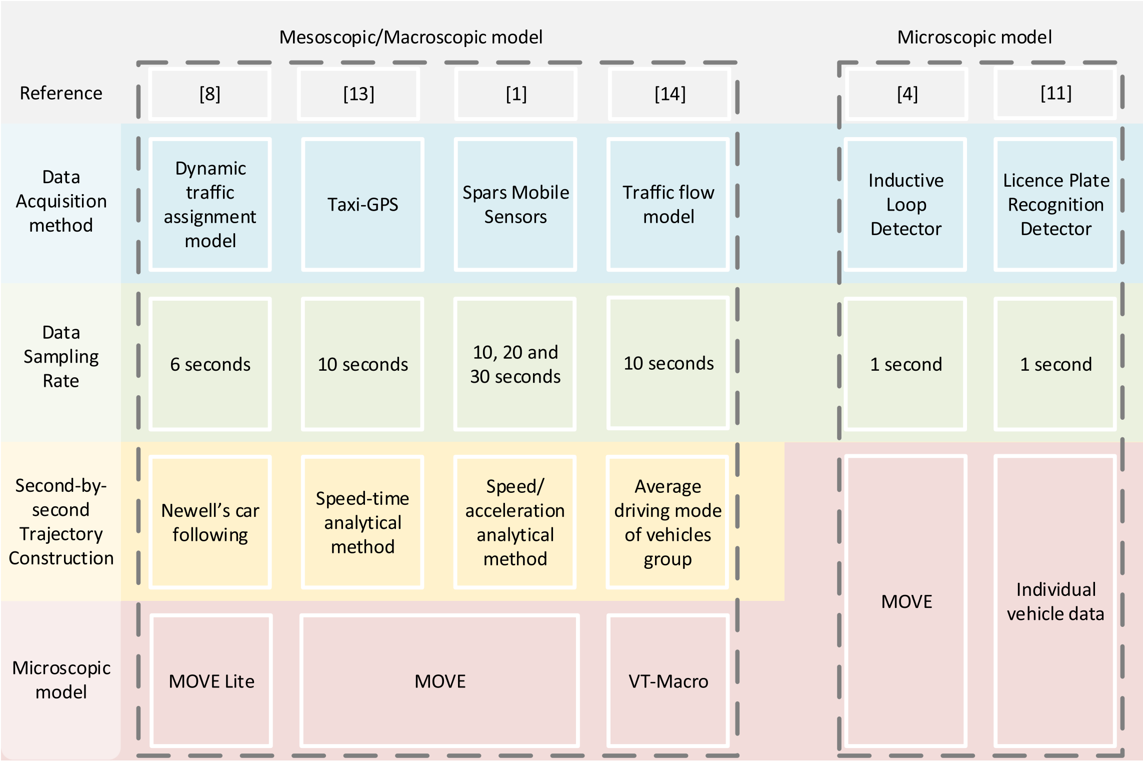

FIGURE 1. A summary of the microscopic, mesoscopic and macroscopic models for vehicular emission estimation.

Emission Simulator (MOVES) from the U.S. Environmental Protection Agency (EPA), Comprehensive modal emission model (CMEM), Passenger car and Heavy duty Emission Model (PHEM), and Virginia Polytechnic Institute and State University microscopic (VT-Micro) model [9], [10], [11]. In [6], a real-time emission estimation system was developed. The proposed system used traffic data collected from inductive loop detectors (ILDs) that provide inductive vehicle signatures to estimate vehicle category and activities. The results, combined with atmospheric conditions, were used to determine the MOVES model's emission rates from pre-generated look-up tables. However, incorrect vehicle type estimation was reported, particularly for single-unit tracks. As a result, inaccurate overall emission estimation is possible due to this misclassification. In addition, the study did not consider other factors, such as vehicle age or road slops, to estimate the emission. The study in [12] estimate individual vehicle emissions by utilizing automatic licence plate recognition (ALPR) detectors to identify vehicle registration data, types, trajectories and deriving modes. The obtained data is used to calculate the emission factors of each vehicle and the aggregate emissions on road links. The study revealed that specific types of vehicles are responsible for high emissions. Therefore, the study recommended applying restriction policies on high-emission vehicles as a remedial action to reduce emissions.

Mesoscopic and macroscopic models reduce vehicles' trajectory data sampling resolution. In [8], the sampling resolution of mesoscopic traffic simulation was reduced to 6 s. Newell's car-following model generated the required second-by-second vehicle trajectory data. The results were fed into a post-processed microscopic MOVES Lite model to estimate emissions. MOVES Lite model considers only five vehicle categories to reduce the computational complexity. The study recognized performance limitations and inaccuracies of Newell's car-following model. In [13], taxi GPS devices collected trajectory data every 10 s. The collected data was then converted into the required second-by-second trajectories to obtain the vehicle-specific power (VSP) and vehicles' operation modes for MOVES. The results showed a difference between U.S. and China emission values. China has higher emission figures due to longer traffic signal cycles that cause longer idle time. In [1], sparse mobile sensor data was used to generate the second-by-second trajectories for emission estimation with the MOVE model. The study examined a range sampling interval (10 s, 20 s, and 30 s). The results showed that acceptable trajectories and emission estimation can be achieved when the sampling interval is less than 20 s. In [14], the Virginia Tech model was used with macroscopic traffic flow. The proposed VT-macro model considered a time resolution of 10 s and driving modes of a group of vehicles instead of individual vehicles. The model estimation emission accuracy exceeded 90% of that achieved by the VT-micro model. Fig.1 summarises the proposed microscopic, mesoscopic and macroscopic model examples.

On-road, on-board/portable or laboratory-based emission monitoring and testing procedures were developed to ensure that manufacturing standards meet emission legislation and policies (e.g. TIER in the U.S. and EURO in Europe) [15]. While the laboratory-based chassis dynamometer method that is run under controllable conditions provides accurate measurements, it does not consider real-world on-road interactive drivers' behaviours, atmospheric and road topographic conditions [15], [16]. Therefore, portable emission measurement systems (PEMS) were developed and used [15], [16]. Sophisticated emission measurements and analysis for emissions type approval require PEMS instruments with large size, weight and power consumption [15]. The study in [17] investigated the viability of characterising vehicle emission dispersion in a real-world street canyon by utilising CO_2 as a tracer gas. A network of air-quality sensors was deployed on the roadside to quantify the dispersion of the tracer gas. The results demonstrated that the CO_2 in a test vehicle's exhaust gas had an insignificant impact at roadside. Work in [18] aimed to apply MOVES model in Korea by considering local topology, driving situations and emissions laws. Hence, expensive and time-consuming real-world emissions tests were conducted for 17 light-duty petrol and diesel vehicles.

The majority of studies leveraged offline traffic data to estimate vehicular emission values. Studies that used real-time measurements conducted high-cost and time consuming measurements. Non of the previous studies suggested a device that uses on-board vehicles' sensors to estimate real-time emission.

2) MACHINE LEARNING ALGORITHMS IN ITS

Recently, there has been an upsurge in the number of research activities that employed machine learning in traffic management [19]. In [20], a transfer learning-based deep RL for vehicle routing was used for urban areas, with four-lanes grid-shaped road networks. The results proved the efficacy of the proposed algorithm in reducing the travel time in a heterogeneous traffic system where automated vehicles (AV) and human-driven vehicles (HV) coexist. The study in [21] used a deep learning long short-term memory network (LSTM) and a bidirectional LSTM (BiLSTM) models-based CO_2 emission estimation. The study used a premeasured offline dataset from Kaggle to train the algorithm. The study in [22] also used different deep-learning techniques that utilize LSTM, gated recurrent unit (GRU), and recurrent neural network (RNN) algorithms to estimate CO_2 emissions. The study relied on premeasured chassis dynamometer test results of 5,287 light-duty vehicles. Both [21] and [22] showed that deep-learning techniques provide an accurate estimation of the CO_2 emission. However, unlike our proposed emission estimation method, the studies [21], [22] did not offer real-time CO_2 emission measurements. In addition, we employ the machine learning algorithm as a remedial action to reduce emissions. All previous research works estimated vehicle emissions to evaluate environmental impact. The majority of these works relied on offline traffic datasets to estimate generic CO_2 emission values. Only a few of these works used real-time traffic measurements to estimate generic CO_2 emission values and recommended remedial action to reduce emissions.

Artificial intelligence (AI) was investigated in transportation systems for traffic management and control [23]. Works in [24], [25], [26], and [27] proposed intelligent traffic management and control schemes. The majority of the previous works focused on controlling traffic signals and intersections. Few of them quantitatively studied the impact of intelligent traffic management and control schemes on CO_2 emissions. None of the previous studies leveraged a learning algorithm with an objective to reduce emissions from petrol and diesel vehicles.

3) APPLICATION OF VEHICULAR COMMUNICATIONS FOR EMISSION REDUCTION

Vehicular communication-based emission reduction techniques were proposed in [28] and [29]. To reduce unnecessary high-emission driving activities such as acceleration and deceleration, inter-vehicle communication (IVC) was proposed in [28]. The study used VT-Micro to evaluate the emission reduction due to the proposed IVC versus traffic light cycle time. When implementing IVC at long (>100 s) traffic light cycle time, lower emission values were observed. Similarly, the impact of communicating traffic light states with vehicles on emission reduction was studied in [29]. The study aimed to optimize vehicles' driving activities and gear choices to reduce emissions when approaching a traffic light. VISSIM simulator and PHEM microscopic model were utilized for traffic flow modelling and emission estimation, respectively. A reduction of 80%, 35%, and 18% in the CO, NOx and particulate matter emission values, respectively, were achieved using the proposed method.

Long range (LoRa) technology is especially proposed for Internet of Things (IoT) devices with limited resources [30]. Given its ability to offer long-distance communication link at a low energy consumption, LoRa presents a promising solution for smart city applications [31]. An experimental study in [32] showed the viability of using Lora technology for vehicular communication networks in highly dynamic urban environments. Similarly, the work in [33] demonstrated the efficacy of LoRa technology in implementing internet-of-vehicles (IoV) network outperforming other technologies in terms of power consumption and coverage range.

B. RESEARCH PROBLEM AND MOTIVATION

The research activities lack a holistic system that estimates real-time emission values from on-road vehicles and takes instantaneous action to reduce them. The urgency of tackling the vehicular carbon footprint to reduce its impact on the environment and climate change mandates prompt action to address the scarcity of this vital system. The main objective and motivation of this study is to propose a practical and comprehensive IoV network that estimates real-time CO_2 emissions from vehicles and takes immediate response

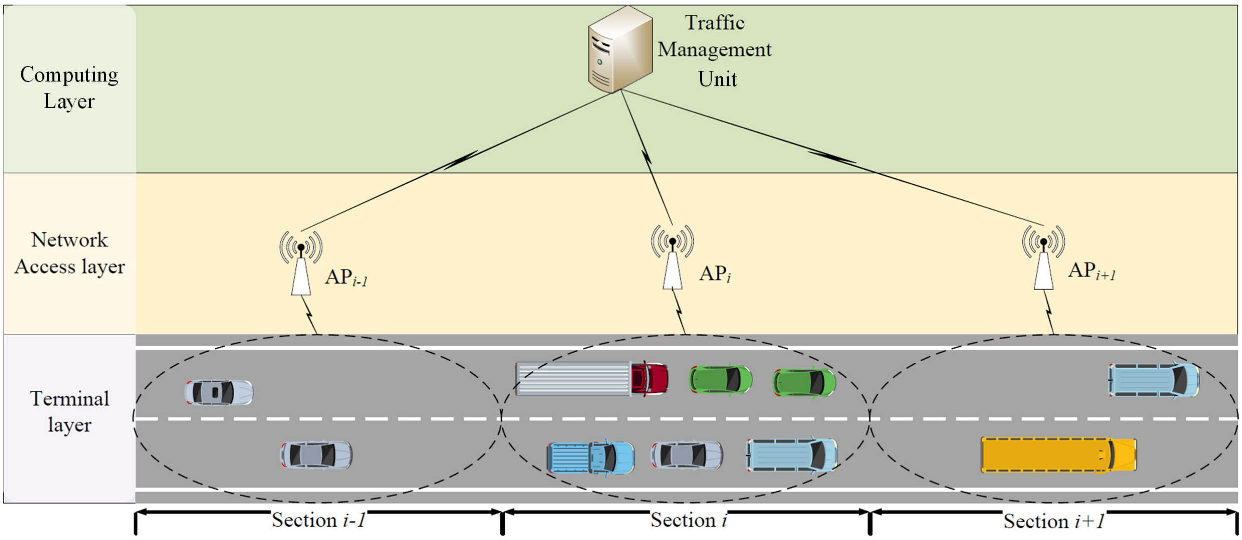

FIGURE 2. A schematic of the proposed IoV network structure.

for emission reduction leveraging reinforcement learning (RL) algorithm as intermediate action toward achieving the net-zero goals for traffic systems.

C. ORIGINAL CONTRIBUTIONS

The original and novel contributions of this paper are:

- Implement an on-board wireless device connects to the vehicle's Electronic Control Units (ECU) via on-board diagnostics-II (OBDII) and uses existing sensors to estimate emission values from the vehicle. This device transmits these values to the network to provide real-time information about traffic-generated emissions. To the best of our knowledge, this is the first work in the literature that proposes real-time data collection of CO_2 emission values for a transport system.
- Propose a RL algorithm for adaptive traffic management and speed limit decisions leveraging the available real-time CO_2 emission values collected from vehicles using the proposed on-board emission estimator. To the best of our knowledge, this is the first study in the literature to propose an RL model with an agent that considers emission levels as a reward, aiming to reduce emissions from petrol and diesel vehicles, which are currently the most available on the roads.

The rest of the paper is organized as follows. The proposed IoV network structure is described in Section II. RL algorithm is explained in Section III. Results are discussed in Section IV. Finally, conclusions are provided in Section V.

II. NETWORK STRUCTURE

Fig. 2 illustrates a schematic of the proposed IoV network structure. The network consists of three layers: vehicles as end network nodes, access points (APs) and traffic management unit (TMU) with edge and/or cloud processing and computing capabilities for traffic-controlling [34], [35]. The following sections present a detailed discussion of these three layers.

A. TERMINAL LAYER: VEHICLES

Vehicles act as end nodes of the network [34], [35]. Each vehicle uses an on-board emission estimation device to measure CO_2 emissions. Existing on-board sensors for vehicle speed, manifold air pressure sensors, air temperature, engine temperature, engine oil pressure, oxygen, and fuel pressure can be used to estimate emissions. The CO_2 emission of vehicle j is calculated as [27] and [36]:

$$E_{jCO_2} = f_{jCO_2}\Delta F_j, \tag{1}$$

where, f_{jCO_2} is the CO_2 rate in (g/ml) of fuel and ΔF_j is the fuel consumption during the time interval of Δt, which is given as [27] and [36]:

$$\Delta F_j = [\alpha_j + \beta_{1j}R_{jT}v_j + (\beta_{2j}M_j a_j^2 v_j/1000)_{a_j>0}]\Delta t, \tag{2}$$

where, v_j is speed (m/s), a_j is acceleration (m/s^2) and R_{jT} is the total tractive force (N) of vehicle j. Vehicle's mass M_j (Kg), α_j, β_{1j} and β_{2j} are vehicle's type-dependent constants. Similarly, other greenhouse gas emissions (GHG) (e.g. CO, HC and NO_x) are estimated with different α_j, β_{1j} and β_{2j} values [27]. As shown in (2), deriving modes v_j and a_j influence the CO_2 emissions.

The estimated emissions volume and vehicle's speed are then sent to the nearest AP using an on-board LoRa transmitter. LoRa technology is an optimal choice for this application since data transmitted from vehicles is latency and power constraint transmission, but it does not require high bandwidth. Furthermore, given the long transmission range offered by LoRa technology, a limited number of APs is adequate, thereby reducing the overall network deployment costs.

B. NETWORK ACCESS LAYER: ACCESS POINTS

APs are road-side units that provide access to the cloud or edge processing units [35], [37], depends on the area and network structure [38] (as explained in Section IV-C). They collect the transmitted emission and speed data from vehicles at that road section and report these values to the TMU. They also monitor and report traffic flow at that road section. APs bring the TMU awareness of the spatial distribution of traffic flow and emission concentrations throughout the network.

The aggregate emission value for a pollutant k on road segment i is proportional to the traffic flow [39], and it is given by:

$$\Delta E_{ik} = \sum_{j=1}^{N_{vi}} E_{jk} T_i, \tag{3}$$

where, E_{jk} is the emission of pollutant k from vehicle j (e.g. emission of CO_2 is given in (1)), T_i is traffic flow (veh/s), and N_{vi} is the number of vehicles on road segment i.

C. COMPUTING LAYER: TRAFFIC MANAGEMENT UNIT

TMU is the computing unit of the network. According to the recent typologies of IoV networks, this unit can leverage edge, fog and/or cloud computing [35], [37], [40]. It collects data from APs to make comprehensive cognition about the network status. The data includes emission values, traffic flow, and vehicle speed in a road segment. As the aggregate emission value on road segment i in (3) depends on the traffic flow, TMU uses the data collected by APs to manage traffic flow and speed on road sections to redistribute and reduce emission values.

The traffic flow T_i is given by the product of vehicle density η (veh/m) and vehicle average speed v (m/s) [39], [41]. Critical traffic density η_c is given by the number of vehicles N_{vi} per road segment i length l_i, which is also reciprocal to the inter-vehicular separation (headway). The traffic is in a free-flow mode if $\eta < \eta_c$. Otherwise, a high traffic flow occurs [39]. As given in (3), road sections with high traffic flow (congestion) are responsible for high emission values. This is because, at high traffic density, the driving mode follows a stop-and-go manoeuvring style, which includes speed fluctuation [1]. Therefore, the TMU aims to control the traffic flow and stabilize the average speed to reduce aggregate emission values.

The following section presents the RL-based emission reduction method.

III. REINFORCEMENT LEARNING-BASED EMISSION REDUCTION

In single-agent RL, the system is modelled as a Markov decision process (MDP), where the agent utilizes a Q-learning algorithm to learn and evaluate the effect of its actions on the system. The agent learns about the system by [42]: *i*) sensing the state of the system, *ii*) taking actions accordingly to stay in the current state or transfer it to a new state, *iii*) receiving a reward to evaluate the quality of this action and *iv*) keeping records about the quality of any state-action pair for future decisions. The agent aims to find a sequence of optimal actions that maximize the total reward.

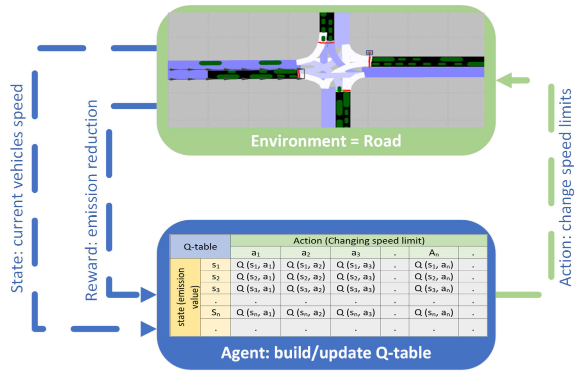

FIGURE 3. A proposed RL algorithm for emission reduction.

Fig. 3 shows a diagram of the proposed RL algorithm for emission reduction. At time step n, the agent perceives the state $s_n \in S$ presented by the speed of vehicles, where S is a finite set of the perceived states. The agent takes an action a_n from a set of possible actions A to maintain or change the current state to a new state, i.e., increase, decrease or maintain the speed limit of a road section under study. The action is taken according to a particular state-action mapping policy. The state-action mapping is performed by exploring different actions for each state or by exploiting a previously used state-action pair that achieved high performance, and it is given as:

$$C_{n+1}(s_n) = \begin{cases} C_n(s_n), & \text{if} \\ \max\limits_{a_n \in A} Q^{n+1}(s_n, a_n) = \max\limits_{a_n \in A} Q^n(s_n, a_n) & \\ a_n, & \text{otherwise} \end{cases} \tag{4}$$

where, $Q^{n+1}(s_n, a_n)$ is the quality of state-action pair. However, (4) is considered a greedy policy because it becomes effective after a sufficient state-action exploration.

ϵ-greedy state-action mapping policy is employed to balance the exploitation and exploration, and it is given as [43]:

$$\tilde{C}_{n+1}(s_n) = \begin{cases} a_n, & \text{if } \epsilon \le e^{-E\alpha} \left(\alpha \in N^+\right) \\ C_n(s_n), & \text{otherwise} \end{cases} \tag{5}$$

where, ϵ is a random number and $e^{-E\alpha}$ is a probability function that decays with a rate of E when the number of visits to a state s_n increases. Hence, this reduces random actions when the exploration becomes sufficient.

The agent considers the level of emissions as a reward R_n to evaluate the quality $Q^n(s_n, a_n)$ of the state transition. If the emission volume on a road section i is ΔE_{ik}, given in (3), the reward of each state is given by:

$$R_n = E_{agr} - \Delta E_{ikn} s_n \tag{6}$$

where E_{agr} is an aggregate emission volume, and the total reward is given by:

$$R = \sum_{n=1}^{\infty} \gamma_n (E_{agr} - \Delta E_{ik} s_n) \tag{7}$$

where $\gamma_n \in [0,1]$ is a discount factor that indicates the significance of the current reward compared to the previously earned values. After receiving the reward, the agent evaluates the updated joint quality of state-action:

$$Q^{n+1}(s_n, a_i) = Q^n(s_n, a_n) + l_r(s, a)[R_{n+1} + \gamma_n \cdot \max[(Q^n(s_{n+1}, a_{n+1})] - Q^n(s_n, a_n)]. \tag{8}$$

where, $l_r(s, a)$ is the learning speed of the agent. It is given as:

$$l_r(s, a) = \left[\frac{1}{1 + V(s, a)(1 - \gamma)}\right]^{0.7}, \tag{9}$$

where $V(s, a)$ is the function of exploitation of a state-action pair. The learning performance in (6) and (7) demonstrates that the agent considers the emission value as a reward for evaluating the quality of state-action transitions in (5). The aggregate emission value obtained in (3) is directly related to the traffic flow on the road segment and, hence, also related to traffic density. In addition, as the agent builds and maintains a Q-table, this means that algorithm implicitly account for historic emission values (from previous action-reward pairs) to take future decisions.

The following section presents the on-board emission meter device design and demonstrates the feasibility of the proposed network in reducing the emission values.

IV. RESULTS AND DISCUSSION

In this study, we implemented a prototype of an on-board emission meter that estimates vehicle's emission and speed values and transmits these values to the TMU, which uses these values to run a RL algorithm. The objective of this RL algorithm is to find adaptive road speed limit values that minimize the aggregate emission values of the network. The following sections discuss the design and test results of the prototype of on-board emission meter device as well as the emission optimization results of the RL algorithm.

A. ON-BOARD EMISSION METER DEVICE PROTOTYPE: DESIGN AND TESTS

1) ON-BOARD EMISSION METER DEVICE DESIGN

Emission values of vehicles depend on different parameters, including speed, fuel consumption, air-fuel mixture during combustion and fuel type. The ECUs of the vehicle provide the sensor parameters [44], [45], which can be processed to estimate emission values. In this study, CO_2 emission values

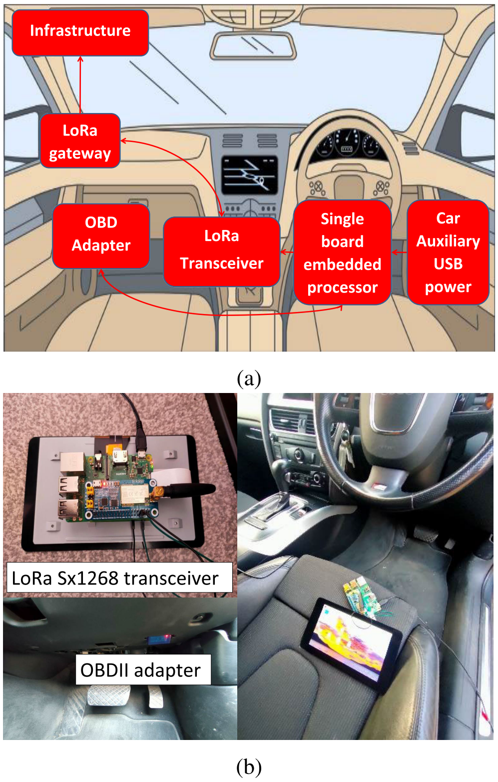

FIGURE 4. On-board emission meter: a) architecture and b) prototype.

were processed and extracted using fuel consumption figures as follows [46, Ch. 6]:

$$CO_{2_{petrol}} = \frac{6.760}{MPG} \quad (kg/km), \tag{10}$$

for a petrol-fuelled vehicle, and

$$CO_{2_{diesel}} = \frac{7.440}{MPG} \quad (kg/km), \tag{11}$$

for a diesel-fuelled vehicle.

Fig. 4 depicts the designed on-board emission meter that was implemented using Raspberry Pi 3B+ equipped with 7'' touchscreen display and LoRa Sx1268 transceiver HAT. The LoRa HAT is placed on the 40 GPIO pins of the Raspberry Pi. The HAT's antenna operates at 433MHz and 868MHz. In our work, we used frequency of 868MHZ which is licence-free in the UK. The Raspberry Pi is powered by an auxiliary USB power outlet adapter (12V to 5V).

On-board vehicle sensors transfer regular readings via Controller Area Network (CAN) protocol (ISO 11898-1 standard) to the ECU of the vehicle using a serial bus [44]. The OBDII uses parameter ID (PID) codes to retrieve sensors readings from the ECU. An OBDII Bluetooth adapter (ELM327) serves as a bridge between OBDII ports and a regular RS232 serial interface. The ELM327 adapter plugs in the 16-pin data link connector (DLC) of the OBDII port and connects with the Raspberry Pi via Bluetooth which allows access to sensors' readings [44].

TABLE 1. Summary of the estimated and standard CO_2 emission values.

Vehicle	Fuel type	Estimated emission value (kg/km)	Standard emission value (kg/km) [46], [47]
BMW 330I 2017	Petrol	0.160	0.170
Citroen C4 2012	Diesel	0.149	0.130

2) ON-BOARD EMISSION METER DEVICE TESTS

The device is tested with two different vehicles on two urban roads in London and Rugby, UK. The first vehicle BMW 330I 2017 has a 2.0-liter (1998 cc) turbocharged inline-4 engine and gross vehicle weight (GVW) of 2,085 kg (4,596 lbs) (approximately). The second vehicle is Citroen C4 2012 with a 1.6L (1560 cc) diesel engine and an approximate GVW of 1,800 kg (3,968 lbs). Table 1 summarizes the estimated and standard CO_2 emission values, while idle[1] [46], [47]. The table shows that the estimated values are within the standard range of emission values. BMW 330I 2017 emission value is closer to the standard value. Meanwhile, Citroen C4 2012 has an emission value higher than the standard value. This is expected because the estimated value varies due to factors such as vehicle age and load.

B. REINFORCEMENT LEARNING-BASED EMISSION REDUCTION RESULTS

At this stage, testing the on-board emission meter to estimate emissions values for a large number of vehicles in the real-world is difficult. Instead, this study used VISSIM to simulate the real-time traffic to examine the performance of the proposed RL algorithm to reduce emissions. VISSIM gives the emissions, speed, and density values of the vehicles on a pre-designed road section of a single lane with 200 km length. The RL algorithm was implemented using Python. A connection between VISSIM and Python was established using Vissim Component Object Model (COM) interface to exchange data related to traffic flow, road network, and simulation outcomes between VISSIM and Python. VISSIM's emissions calculation model determines the emissions values for each vehicle according to (1) and (2). The produced dataset is utilized to train the RL agent over 1000 episodes with a learning speed $l_r = 0.7$, epsilon $\epsilon = 0.2$, discount factor $\gamma = 0.8$, and epsilon-decay $E = 0.005$. These values were tuned to optimize the learning convergence of the RL algorithm. Otherwise, using different values does not provide the expected performance [20].

Fig. 5 shows the predicted speed and emission values under high traffic flow of 2000 vehicles/h and traffic density of 112 vehicles/km/lane. The figure illustrates that the mean speed values after applying the RL algorithm are similar to the speed values before applying the RL. The RL algorithm restricted the variation of the speed within maximum and minimum values of 46.9 km/h and 47.1 km/h, respectively. The total CO_2 emission values decreased from 978 kg and 1003 kg to 827 kg and 866 kg during the first and second hours, respectively. This is equivalent to an average emission reduction of 150 kg/h. The result is consistent with [1] that reported if all vehicles cruise in a cluster of constant speed, this reduces the emission values. However, the RL suggested precise speed restriction is difficult to achieve practically using the current cruise control and ECUs that support 1 km/h of increments or decrements.

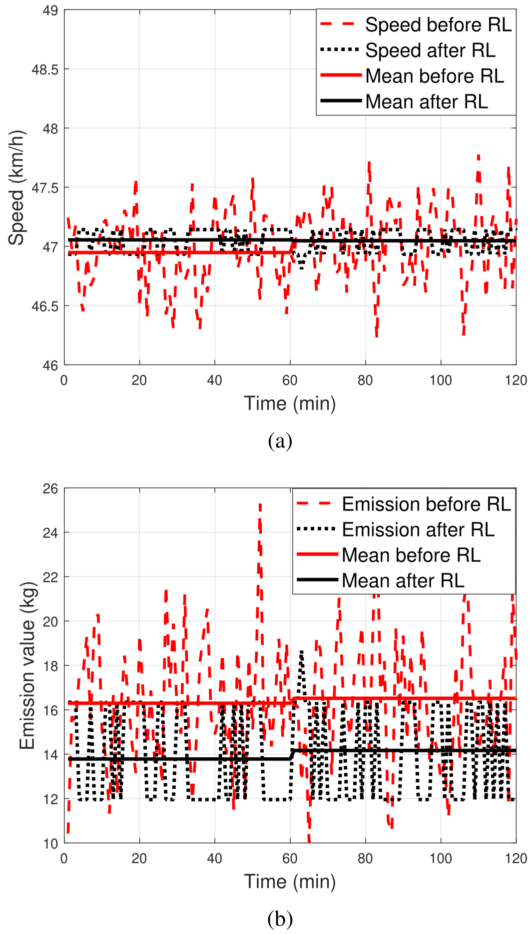

FIGURE 5. Values of a) speed & b) emissions before and after applying the RL under high traffic flow conditions with a traffic density of 112 vehicles/km/lane.

The predicted speed and emission values under free flow traffic of 1500 vehicle/h and density of 48 vehicles/km/lane are depicted in Fig. 6. Similar to the high traffic flow case, the algorithm restricted the speed values between 96.1 km/h and 94.7 km/h. This results in a CO_2 emission reduction from 512 kg to 501 kg and from 530 kg to 488 kg, i.e. the average emission reduction values are 11 kg/h and 42 kg/h during the first and second hours, respectively. Those values are lower than the achieved reduction during high traffic density because the speed values vary over a wider range due to the free flow. In addition, the emission values in this case are low and further reduction of the emission values by changing the speed values is limited. The results also meet the expectations in (3), which linked traffic flow and emission values. Fig. 6 (b) depicts that the emission values when the traffic is in a

[1]Due to safety constraints according to Coventry University ethics applications: P154637 and P144636.

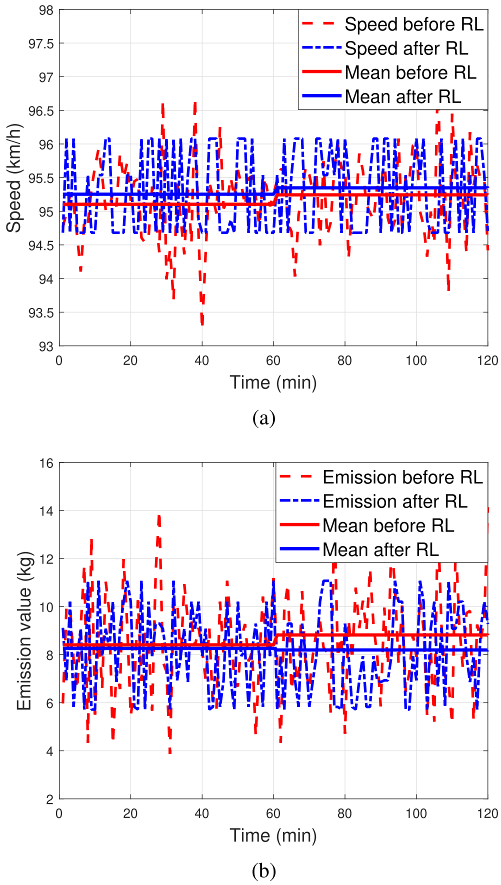

FIGURE 6. **Values of a) speed & b) emissions before and after applying the RL under free-flow traffic conditions with a traffic density of 48 vehicles/km/lane.**

free-flow mode are lower than those in Fig. 5 (b) when the traffic flow is high.

Having presented the results of the RL algorithm, the next section discusses the network scalability and practical implementation. It provides future directions to underpin the practicality of the proposed system.

C. RESULTS DISCUSSION: NETWORK SCALABILITY, PRACTICAL IMPLEMENTATION AND FUTURE DIRECTIONS

Practical implementation of the proposed IoV network needs to consider four factors: the transmission range of LoRa, type of area, architecture of traffic management system and the complexity of the RL model.

The experimental study in [32] showed an adequate performance of LoRa technology at a transmission range of 0.2 km, which is close to the length of urban road link. Our results were obtained from 200 km single-lane road section in VISSIM and the training happened over 1000 episodes. In a more complex network scenario, in [20], urban areas of 1 km^2, 1.96 km^2 and 4 km^2, with four-lanes grid-shaped road networks of 3×3, 5×5 and 8×8, the training required 1500, 2500 and 9000 episodes, respectively. The processing capacity of the network can be handled by the network structure. For example, considering a realistic traffic management system implemented in the USA [38], APs along a single road or highway can report to a single facility TMU. In a small city, APs can report the collected data to a single jurisdiction TMU. In large metropolitan cities, multiple jurisdictions TMUs are required to manage traffic of different areas. However, the studies in [48] and [49] showed that managing the traffic in a particular area impacts the traffic in other areas, creating a bottleneck. Thus, as a solution multiple jurisdictions TMUs need to cooperatively manage the traffic. Therefore, a future direction of this study is to investigate a cooperative multiple agents machine learning algorithm to manage the traffic with an objective to reduce the CO_2 emissions at network level.

In addition, the proposed structure of the IoV network does not depend on the vehicle type, meaning it can collect data from any type of vehicle on the road. However, the on-board emission meter was tested with petrol- and diesel-fueled vehicles in Section IV-B. The device was not tested with other types of vehicles, such as hybrid and electric vehicles. A future direction of this study is to extend the design of the proposed on-board emission device to report emission data from hybrid vehicles to the network.

V. CONCLUSION

In this paper, we developed a holistic system to determine real-time vehicular CO_2 emission values and developed RL-based adaptive speed limits to reduce the total emission of the network. We demonstrated an on-board device that estimates vehicle emission values and transmits them to the network. The device was tested with petrol and diesel vehicles. The estimated CO_2 emission values were close to the standard emission values for the tested vehicles, with a difference attributed to the vehicle's age and loading. The study relies on interaction between VISSIM and Python simulations to obtain emissions values and apply the machine learning algorithm. The results showed that the machine learning algorithm did not change the speed value under high traffic flow but reduced the variation of the speed values. This achieved a reduction of 150 kg/h of average CO_2 emission values when the speed of the vehicles can be controlled to one decimal point accuracy. The achieved emission reduction under free flow was limited to 42 kg/h because the emission values were low, and achieving more reduction by restricting the speed values is not sufficient. More efforts are required to develop an efficient emission reduction algorithm that considers traffic flow and density at network level.

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