Carbon Emission-based Toll Taxation System: Leveraging OBD-II Sensor Data and Algorithmic Analysis

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***Abstract*—Addressing the pressing issue of climate change requires a comprehensive understanding of the environmental impact of individual actions, particularly in the domain of personal transportation. Despite increasing global awareness, there remains a significant lack of understanding among individuals regarding the carbon footprint generated by their daily transportation choices.**

In response to this challenge, our project presents a novel approach to mitigate CO_2 emissions in personal transportation. Leveraging the precise parameters measured by OBD-II sensors and employing an algorithmic model, we derive accurate estimations of CO_2 emissions produced by vehicles. Subsequently, we propose the implementation of a toll tax system, utilizing these emission values as a basis for calculation. This system incentivizes eco-conscious behavior among drivers, prompting them to consider the environmental cost of their journeys. Through this integrated approach, our research aims to not only enhance the understanding of CO_2 emissions in personal transportation but also to foster a culture of sustainability and environmental responsibility.

***Index Terms*—carbon footprint, Air to fuel Ratio(AFR), On-Board diagnostics(OBD), Toll Tax System, Parameter ID (PID).**

I. INTRODUCTION

TRANSPORTATION serves as the backbone of modern civilization, facilitating mobility and economic activity worldwide. However, its convenience comes at a significant environmental cost, with transportation accounting for a substantial portion of global CO_2 emissions, a major contributor to climate change. Despite growing awareness, many individuals remain unaware of the environmental impact of their transportation choices, impeding effective climate action. With transportation alone responsible for nearly one-fifth of global CO_2 emissions and CO_2 contributing to a staggering 74% of all greenhouse gas emissions as of 2021, the imperative to bridge this awareness-action gap is undeniable.

Amidst this environmental challenge, a considerable number of vehicles in society were developed before the widespread adoption of modern digital electronics. These vehicles lack post-driving digital feedback mechanisms, limiting drivers' awareness of their driving habits. However, cars manufactured after 2001 in the EU(European Union) are equipped with sockets for the OBD-II or EOBD standard. This standard enables the collection of data such as gear usage, fuel economy, and RPM, allowing for digital data to be transmitted to a computer or cloud for processing. Moreover, recognizing the urgency of addressing vehicular emissions, the Government of India mandated all vehicles to be fitted with an OBD as part of the Bharat Stage 6 (BS6) emission norms, effective from April 1, 2020.

Building upon this technological foundation, an innovative idea has emerged: to develop a monitor that reads data from an OBD-II and processes it to provide drivers with feedback on the environmental impact of their car journeys. This feedback aims to empower drivers with insights for improvement, enhancing environmental consciousness.

A. Problem Statement

Climate change poses a significant global challenge, necessitating a comprehensive understanding of the environmental impact of individual actions, particularly within the realm of personal transportation. Despite increasing awareness, there persists a substantial gap in knowledge among individuals regarding the carbon footprint generated by their daily transportation choices.

Addressing this challenge requires a multifaceted approach aimed at mitigating CO_2 emissions in personal transportation. Currently, there is a lack of precise methodologies to accurately estimate the CO_2 emissions produced by vehicles on a per-journey basis. Furthermore, existing initiatives to incentivize eco-conscious behavior among drivers often lack effectiveness and scalability.

B. Relevant Works

Measuring vehicular emissions has been an area of active research, with several studies exploring the use of On-Board Diagnostics (OBD) data for this purpose. Caubyn et al. [1] developed a methodology to estimate real-world fuel consumption and emissions using OBD-II data, demonstrating the potential of this approach for monitoring and reducing emissions. Similarly, Ropkins et al. [2] utilized OBD data to estimate real-world emissions from light-duty vehicles, highlighting the importance of accurate emission measurements for policy development.

The integration of OBD data with advanced algorithms and models has been a focus area for researchers. Graver et al. [3] proposed a machine learning-based approach to predict real-world emissions using OBD data, achieving high accuracy in their estimations. Gao and Kaas [4] developed a model for estimating emissions based on OBD data and driving patterns, enabling personalized feedback and recommendations for eco-driving.

Several studies have explored the use of incentives and pricing mechanisms to encourage eco-friendly driving behavior. Boriboonsomsin et al. [5] investigated the potential of eco-driving incentive systems, demonstrating their effectiveness in reducing emissions and fuel consumption. Litman [6] examined the role of road pricing strategies, such as distance-based fees and emissions-based charges, in promoting sustainable transportation choices.

Researchers have also explored the integration of OBD data with external data sources and emerging technologies. Dey et al. [7] proposed a framework for combining OBD data with GPS and environmental data to provide real-time emissions monitoring and eco-routing recommendations. Huang et al. [8] explored the use of connected vehicle technologies and cloud computing for real-time emissions monitoring and management.

While these studies have made significant contributions, there remains a need for comprehensive solutions that combine accurate emission measurement, personalized feedback, and effective incentive mechanisms to drive behavioral change in personal transportation. Additionally, the integration of emerging technologies, such as machine learning and cloud computing, presents opportunities for more advanced and scalable solutions.

C. *Our Contributions*

We have addressed a prevailing issue with existing solutions that lack efficiency, accuracy, and cost-effectiveness. Moreover, these solutions fail to sufficiently account for the disparity in emissions between various vehicle types, such as SUVs and hatchbacks. By integrating our solution with the toll tax system, we aim to incentivize individuals to contribute to environmental preservation. Recognizing the multitude of sources contributing to air pollution and global warming, our focus rests on vehicular emissions, the most rapidly escalating contributor. Our innovation represents a pivotal step towards empowering individuals to combat this pressing environmental challenge.

II. PROPOSED APPROACH

The proposed system consists of three main components: The first one is data collection using ELM327 from the OBD2 interface. In the second part, we have used appropriate data to calculate the fuel consumption and CO_2 emission from collected data using an efficient algorithm. At last, We proposed a Toll tax management system based on the emissions data we have calculated. We dynamically adjusted toll rates according to vehicle emissions, aiming to encourage low-emission vehicles and discourage high-emission ones.

A. *Data Collection*

We have used the OBD-II interface, ELM327 module, Arduino nano, HC05 Bluetooth module for collecting real-time data on the vehicle. The description of each component is as below :

OBD-II Interface: OBD-II stands for On-Board Diagnostics, which is a standardized system in vehicles to monitor their performance and diagnose issues.OBD-II interfaces use a standardized protocol to communicate with vehicles, making it easier for different devices to work with a wide range of cars.

ELM327: It's a small device that connects to a car's OBD-II port and communicates with the onboard computer. It's like a translator, allowing external devices to understand the data from the car's computer.

HC05: It a Bluetooth module used to get data from OBD to Arduino Nano. This device is used because it is compatible with the ELM327 module.

Arduino Nano: It is a well-known Wi-Fi-enabled micro-controller. It is used to get data from ELM327 via Bluetooth module and send it to the cloud using MQTT or any other protocol.

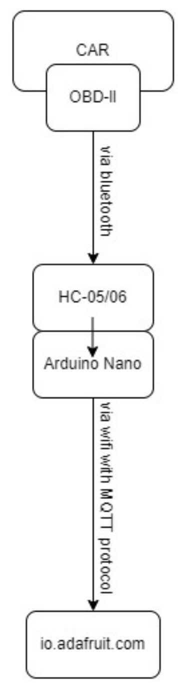

Fig. 1: Data flow diagram

In Fig. 1, we can see how data is collected step by step using this configuration.

Using the above configurations and components, we have collected many parameters from the OBD-II port that are useful for the calculation of emissions like Engine RPM, Vehicle Speed, Throttle Position, Coolant Temperature, Mass Air Flow(MAF), Oxygen Sensor data, etc.

This data will be uploaded to the cloud platform of Aadafruit.io via Arduino Nano.

B. *Emission calculation*

To quantify the carbon emissions of vehicles in real-world driving scenarios, we utilized data retrieved from the On-Board

Diagnostics II (OBD-II) sensor, specifically the ELM327. The OBD-II sensor provides access to various parameters crucial for assessing vehicle performance and emissions levels. We can get the sensor data by an API call to our cloud database. The process of calculating carbon emissions involves estimating fuel consumption, which serves as a proxy for emissions. Fuel consumption is influenced by multiple factors, including engine speed (RPM), vehicle speed, throttle position, coolant temperature, air-to-fuel ratio (AFR), and engine load. In addition, we calculated the air-fuel ratio using the O2 sensor readings and incorporated this important information into our emissions calculation process.
We calculate the fuel consumption in liters per km using the following empirical formula:

$$\begin{aligned}\text{fuelConsumption} &= \alpha \times \text{rpm} \times \\ &\text{throttle} \times (1 + 0.0016 \times \text{speed}) \times \rho \end{aligned} \tag{1}$$

where α is the fuel consumption constant and ρ is Density of gasoline in kg/liter. The value 0.0016 is a coefficient used to adjust fuel consumption based on vehicle speed. It reflects factors like aerodynamic drag and engine efficiency.

We also count the coolant temperature and engine load in the fuel consumption. Lower AFR results in higher consumption. So, we have also added the effect of AFR(air-to-fuel ratio) in our algorithm. We will adjust the fuel consumption for deviation from stoichiometric AFR.

$$\begin{aligned}\text{fuelConsumption} &= \text{fuelConsumption} \times \\ &(1 - 0.02 \times (\text{coolantTemp} - 90)) \end{aligned} \tag{2}$$

$$\begin{aligned}\text{fuelConsumption} &= \text{fuelConsumption} \times \\ &(1 + 0.01 \times \text{engineLoad}) \end{aligned} \tag{3}$$

$$\text{fuelConsumption} = \text{fuelConsumption} \times \frac{14.7}{\text{afr}} \tag{4}$$

The value of 0.02 represents the rate at which fuel consumption changes per degree Celsius deviation from the optimal coolant temperature of 90 degrees Celsius. The equation subtracts 90 degrees Celsius from the coolant temperature to determine the deviation from the optimal temperature.

The value of 0.01 in the equation adjusts fuel consumption based on engine load. It represents the rate at which fuel consumption changes per unit increase in engine load, reflecting the impact of engine workload on fuel usage.
Adjustments are made to the fuel consumption based on the deviation of the estimated AFR from the stoichiometric AFR (14.7 for gasoline).

To improve the accuracy of our calculations, we use mapping to count the impact of throttle position. We are mapping the throttle range from 0-100 to a narrower range of 0-70.

After calculating the fuel consumption, we will calculate the CO_2 emissions.

$$CO_2 \text{ Emissions} = \text{fuelConsumption} \times 1000 \times \gamma \tag{5}$$

Where γ is the CO_2 emissions per unit fuel. 2.31 kg/L is a commonly used average emission factor for gasoline in many emissions estimation models and regulatory frameworks.

C. Toll Tax Management System

The proposed system introduces an emission tax that is calculated based on the carbon emissions produced by a vehicle during a particular trip. This emission tax amount will then be added to the existing regular toll tax at toll plazas.

The emission tax is computed using the following formula:

$$\begin{aligned}\text{Emission Tax} &= (\text{Total Distance}) \times (\text{Average Emission Rate}) \\ &\times (\text{Emission Factor})\end{aligned} \tag{6}$$

where:

- Total Distance (in km) = Average Speed (km/h) × (Engine Run Time (h)
- Average Emission Rate (in g/km) = Average rate of carbon emissions per kilometer during the trip, calculated from fuel consumption estimates based on OBD-II data like RPM, throttle position, coolant temperature, and air-fuel ratio.
- Emission Factor is a constant that determines the monetary value associated with each gram of carbon emissions. It essentially translates the emissions into a financial cost.

The calculation process is as follows:

1) At the start of each trip, the current emission tax value is initialized to zero.
2) During the trip, the system collects real-time OBD-II sensor data and uses an algorithmic model to estimate fuel consumption and carbon emissions.
3) The Average Emission Rate is calculated by averaging the emission values over the entire trip.
4) The Total Distance is calculated from the Average Speed and Engine Run Time.
5) The current Emission Tax is computed using the formula: Emission Tax = (Total Distance) × (Emission Factor) × (Average Emission Rate).
6) At the end of the trip, this current emission tax value is then added to the total emission tax.
7) Now, upon reaching a toll plaza, your total payable tax will be calculated as the total emission tax added to the regular road tax of that particular road.
8) Once you pay your toll tax, the total tax is set to zero, and it will keep increasing based on your next trips until you reach the toll plaza next time.

By adding this emission tax to the regular toll tax, vehicles that produce higher carbon emissions during a trip will be charged a higher overall toll. This creates a financial incentive for drivers to adopt eco-friendly driving practices and choose lower-emission vehicles, as it directly impacts the toll cost they have to pay.

III. Algorithm

We have created an algorithm to calculate carbon emissions. The algorithm begins by initializing constants essential for fuel consumption calculation. These constants include the density of gasoline, the fuel consumption constant, the air density at sea level, and the engine displacement.

Algorithm 1 Algorithm to Calculate Fuel Consumption

1: Adjust Throttle Position:
$throttle \leftarrow map(throttle, 0, 100, 0, 70)$ {Map throttle range from 0-100 to 0-70}
2: Calculate Fuel Consumption:
$fuelConsumption \leftarrow FUEL\_CONS\_MULT \times rpm \times throttle \times (1 + 0.0016 \times speed) \times FUEL\_DENSITY\_GASOLINE$
3: Adjust Fuel Consumption based on Coolant Temperature:
$fuelConsumption \times = (1 - 0.02 \times (coolantTemp - 90))$ {Adjust for temperature deviation from 90 Celsius}
4: Adjust Fuel Consumption based on Engine Load:
$fuelConsumption \times = (1 + 0.01 \times engineLoad)$ {Adjust for engine load}
5: Adjust Fuel Consumption based on Air-Fuel Ratio (AFR):
$fuelConsumption \times = (14.7/afr)$ {Adjust for deviation from stoichiometric AFR}
6: **return** Fuel Consumption: $fuelConsumption$ {Return the calculated fuel consumption in liters per kilometer}

Here's a brief explanation of the constants used in calculating the FuelConsumption :
1. FUEL_DENSITY_GASOLINE: It represents gasoline density in kg/l and converts fuel consumption from liters to kilograms.
2. FUEL_CONS_MULT: It is a multiplier factor for fuel consumption. It's derived empirically from engine parameters.
3. FUEL_CONS_AIR_DENSITY: Air density at sea level in kg/m^3. Used to adjust fuel consumption for air density changes.
4. ENGINE_DISPLACEMENT: Represents engine volume in liters. It represents total air/fuel mixture volume per engine cycle. It normalizes fuel consumption based on engine size.

After calculating the fuel consumption from this algorithm, we will calculate the CO_2 emissions from equation (5)

IV. Discussion and Remarks

In our analysis, initially, we explored the GPS-based method, which relies on data such as traveled distance, speed, and acceleration. However, we found this method to be limited in accuracy as it overlooks critical factors like engine load, fuel type, RPM, and vehicle condition. Furthermore, it cannot differentiate between vehicle types.

Next, we investigated the ML-based method, which involves training a long short-term memory (LSTM) model on existing public data of vehicles. While this method offers improved accuracy compared to the GPS-based approach, it has its drawbacks. It cannot provide real-time carbon footprint readings, relies on existing data that may not include newly launched vehicles, and may not accurately account for variations in engine conditions.

Finally, we implemented the OBD2 protocol-based method. This method utilizes real-time engine parameters obtained through the OBD2 protocol, offering significantly higher accuracy in estimating carbon footprint. Unlike the previous methods, the OBD2 protocol-based approach can differentiate between vehicle types and models, does not rely on existing data, and works for newly launched vehicle models. Moreover, it provides precise results by considering real-time engine conditions.

We would have used a machine learning model which can be trained on existing datasets of different vehicle's pollution emission data and it's parameters by which we can generate our own pollution calculation function which can be further used to calculate emissions from collected data.

In conclusion, after analyzing these methods, we found that the OBD2 protocol-based approach is the most accurate and reliable method for estimating vehicle carbon footprint. By leveraging real-time engine data, it overcomes the limitations of the GPS-based and ML-based methods, providing precise estimates for various vehicle types and conditions.

V. Numerical Results

In our evaluation of CO_2 emission estimation accuracy, we utilized multiple datasets derived from OBD-II parameters to calculate CO_2 emissions using our algorithm. As a result, our algorithm generated emissions estimates ranging from 170-230 grams per kilometer (g/km). These estimates, derived from comprehensive OBD-II monitoring data, offer a notable advantage over existing methodologies. While falling near the range provided by the literature [9] (120 to 170 g/km), our algorithm's estimates represent a refinement due to their basis on real-time engine and vehicle parameters rather than relying solely on fuel type and vehicle classification. Furthermore, our algorithm's estimates present a more precise and targeted approach compared to the broader spectrum literature [10](170 to 290 g/km) which is also calculated based on fuel type. This validation underscores the robustness and reliability of our algorithm, positioning it as a promising tool for accurately estimating emissions from vehicles across diverse driving conditions and vehicle types.

VI. Future scope

By leveraging a machine learning model trained on an extensive dataset comprising pollution emission data sourced from a wide range of vehicles, alongside their associated parameters, we can unlock the potential to craft a bespoke pollution calculation algorithm. This algorithm would be meticulously fine-tuned to address our unique requirements and objectives. Subsequently, armed with this algorithm, we can effectively estimate emissions by analyzing the data collected from our target sources. This approach not only streamlines the emission estimation process but also enhances its accuracy and adaptability to diverse scenarios and contexts.

VII. Conclusion

The proposed Carbon Emission-based Toll Taxation System represents a novel and comprehensive approach to mitigating vehicular CO_2 emissions and promoting sustainable transportation practices. By leveraging the rich data available through the OBD-II interface and employing an advanced algorithmic model, we have demonstrated the capability to accurately estimate real-time CO_2 emissions from personal vehicles.

The integration of multiple parameters, including RPM, vehicle speed, throttle position, coolant temperature, mass air flow, and air-fuel ratio, enables our system to provide precise emission calculations tailored to individual driving patterns and conditions. This level of granularity is crucial for fostering environmental awareness and empowering drivers to make informed decisions regarding their carbon footprint.

Furthermore, our innovative toll taxation system introduces a powerful incentive mechanism to encourage eco-conscious behavior among drivers. By dynamically adjusting toll rates based on a vehicle's emission levels, we create a financial motivation for individuals to opt for lower-emission transportation choices. This approach not only promotes immediate emission reductions but also drives long-term behavioral changes, facilitating a broader societal shift towards sustainable mobility.

The successful implementation of this system holds the potential to have a significant impact on mitigating the environmental consequences of personal transportation. By bridging the gap between awareness and action, we empower individuals to make tangible contributions toward combating climate change through their daily transportation choices.

While the proposed system represents a promising step forward, further research and development are necessary to address potential challenges, such as scalability, data privacy concerns, and integration with existing transportation infrastructure. Additionally, ongoing efforts to refine the algorithmic models and incorporate emerging technologies, such as machine learning and connected vehicle systems, will enhance the system's accuracy and effectiveness.

In conclusion, tackling climate change demands a multifaceted strategy involving technological advancements, policy measures, and changes in human behavior. The proposed Carbon Emission-based Toll Taxation System combines these elements into an integrated solution that promotes sustainable transportation practices and reduces vehicular emissions contributing to climate change.

Appendix A
OBD-II Sensor

A. OBD-II Sensor Data Fields Description

1. **ENGINE_RPM:** Engine RPM (revolutions per minute) is a measure of how fast the engine's crankshaft is rotating. It indicates the speed at which the engine's pistons are moving up and down in the cylinders.

2. **VEHICLE_SPEED:** Vehicle speed is the speed at which the vehicle is traveling, typically measured in kilometers per hour (km/h) or miles per hour (mph).

3. **THROTTLE:** Throttle position refers to the angle of the throttle valve inside the engine's throttle body. It indicates how open or closed the throttle valve is, which controls the amount of air entering the engine.

4. **ENGINE_LOAD:** Engine load is a measure of how much work the engine is performing relative to its maximum capacity. It is typically expressed as a percentage and can provide insights into the engine's operating conditions.

5. **COOLANT_TEMPERATURE:** Coolant temperature is the temperature of the engine coolant, which helps regulate the engine's operating temperature. It is an important parameter for monitoring engine health and performance.

6. **FUEL_AIR_COMMANDED_EQUIV_RATIO:** The fuel-to-air commanded equivalence ratio is a measure of the air-fuel mixture's richness or leanness compared to the stoichiometric ratio. It indicates how much fuel is being injected into the engine relative to the amount of air available for combustion.

B. OBD-II PIDs

PID (hex)	PID (dec)	Data bytes returned	Description
04	4	1	Engine coolant
05	5	1	Calculated engine load
0D	13	1	Vehicle Speed
10	16	2	Mass Air Flow
11	17	1	Throttle position
1F	31	2	Run time since engine start

TABLE I: PID values and descriptions.

C. URLs

GitHub Link of our project which includes the python code of the calculation, dataset files and Arduino code for: GitHub Repository

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