IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

EMISSION CONTROL IN AUTOMOBILE USING BLACK BOX

Sneh Prabha

Student

Indira Gandhi University,Meerpur,Rewari (Haryana)

ABSTRACT

More and more vehicles are equipped with in-vehicle monitoring systems, and there are now a wide variety of these systems on the market. For the most part it serves as a feedback system for drivers and others by keeping tabs on things like how they drive, when they drive, and where they drive it. Many also give in-vehicle notifications if pre-set limits are violated (for example, hard acceleration). It is the driver's behaviour on the road that is being watched, such as speed or the severity of the incident (for example, seat belt use). When a motorist's propensity to engage in certain behaviours is tracked, the system may provide a risk assessment for that driver. It may also make it possible to find ways to lessen the likelihood of a car accident for the driver. We will investigate the use of a black box to reduce emissions in automobiles in this research report.

Keywords: Emission, Control, Automobile, Black box.

INTRODUCTION

Black boxes are increasingly being used by automakers to regulate emissions. This is an efficient method for reducing air pollution and protecting the environment.

Monitor fuel usage and other metrics in autos by using black boxes. Besides that, it keeps a log of the driver's actions. When you come to a complete stop at a red light or stop sign, the black box automatically shuts off the engine to prevent pollution.

The black box is an equipment that records the data of a vehicle in order to manage the emissions of automobiles. Use the black box to monitor fuel consumption and other important information.

All driving-related data from a car is recorded in a black box. Speed, engine power, and other vehicle-related data such as fuel consumption and acceleration are included in this information. It also keeps track of when and how long an engine has been operating.

Large vehicles, such as trucks, buses, and aircraft, often use black boxes. In order to reduce emissions, the black box provides car owners with a comprehensive report on their fuel use and other pertinent information about their driving patterns.

To keep tabs on pollution, automakers rely on black boxes. In a black box, all the information about the automobile is recorded, including the driving circumstances, fuel consumption, and performance of the engine, among other things.

On-board and off-board sensors are used in an automobile's pollution control system. Off-board sensors, such as air quality monitors and weather stations, are connected to or located around the vehicle's engine, whereas on-board sensors are built into the vehicle itself.

A black box is a device that's been in use for decades. But it wasn't until General Motors introduced pollution control technology with the black box in 1989 that manufacturers began utilising them to monitor vehicle performance.

With black box technology, there are several applications, from lowering pollution to increasing safety.

Air pollution is exacerbated by automobile emissions. Automobile manufacturers utilise black box data to create and upgrade their vehicles in order to cut emissions.

Emissions from a car are controlled by a mechanism known as an automotive emission control system. Pollutant emissions are reduced, and this has a positive impact on the environment. There are several components and sensors that collect data about the engine's functioning and then utilise it to calculate how much fuel to inject and whether or not to activate further emission controls, such as catalytic converters or particle filters.

Electronic control units (ECUs) are the most prevalent form of automated emission control systems, and they employ an on-board computer and sensors, such as an O2 or lambda sensor, to directly detect engine speed.

Developed nations like the United States are mandating the use of black box technology in all vehicles as a means of ensuring the safety and security of passengers. Only the most critical data, such as vehicle speed, temperature, and position, is recorded by these automotive black boxes. The data gathered by a vehicle's black box may aid in the investigation and management of automobile accidents. Researchers believe that autos equipped with a Black Box might go a long way toward ensuring the safety of the travelling public.

More than a million people die each year as a result of transportation-related accidents, according to the WHO. The black box system drew the first step toward resolving the issue in order to respond to this circumstance. "Black Box" technology, which is similar to the data recorders used in planes, may now be an important tool in the investigation of car accidents.

Electronic devices that capture data in the case of an accident are already standard equipment in a large percentage of automobiles on the road. That's why it's so critical to have backup recorders that can objectively document what happens in cars before, during, and after a collision. Input from witnesses, victims, and police reports that is often subjective.

The correct reason of a system crash may be discovered by applying the system crash investigation. Bringing Black Box technology to cars is made possible in large part by the automotive electronics industry, often referred to as "Autotronics." The majority of this system's resources are devoted to two areas. Detecting and collecting data from a vehicle is the first step. The second consideration is how to make the data easier to understand for the user.

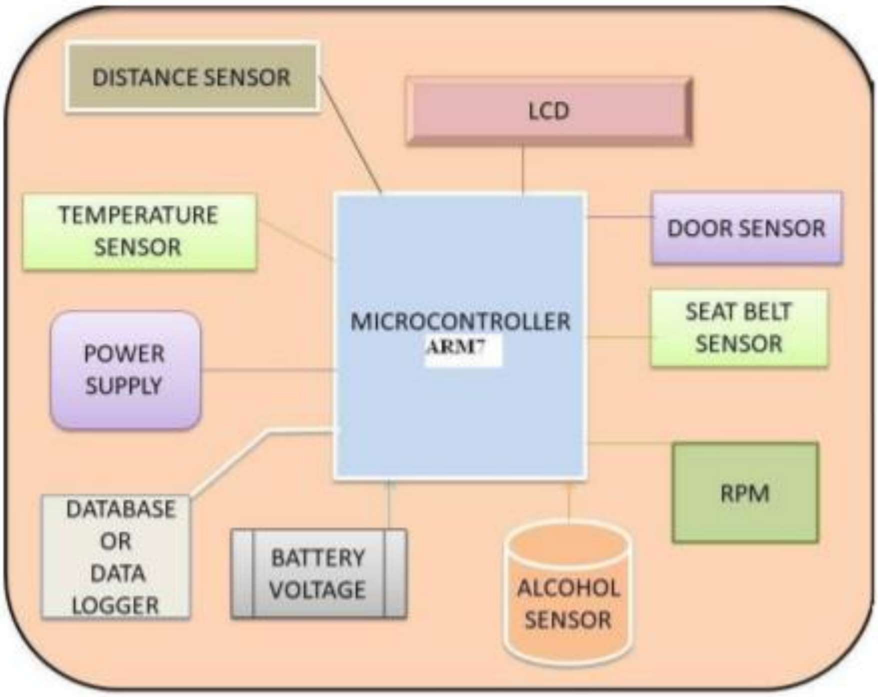
The first portion requires a wide range of components and sensors. Second, a USB module was used to save the data using a pen drive or memory stick, and this is how the log data was collected. This system consists of two major components. The first is to keep track of your car's speed, temperature, time, and position; the second is to use the hard drive's data to figure out precisely what occurred during the incident.

Many cities have a high rate of car accidents on a daily basis. Poor driving habits, such as speeding, drinking, and riding without safety gear, are to blame for the rise in this issue. According to statistics, more people die in vehicle accidents than in airline crashes.

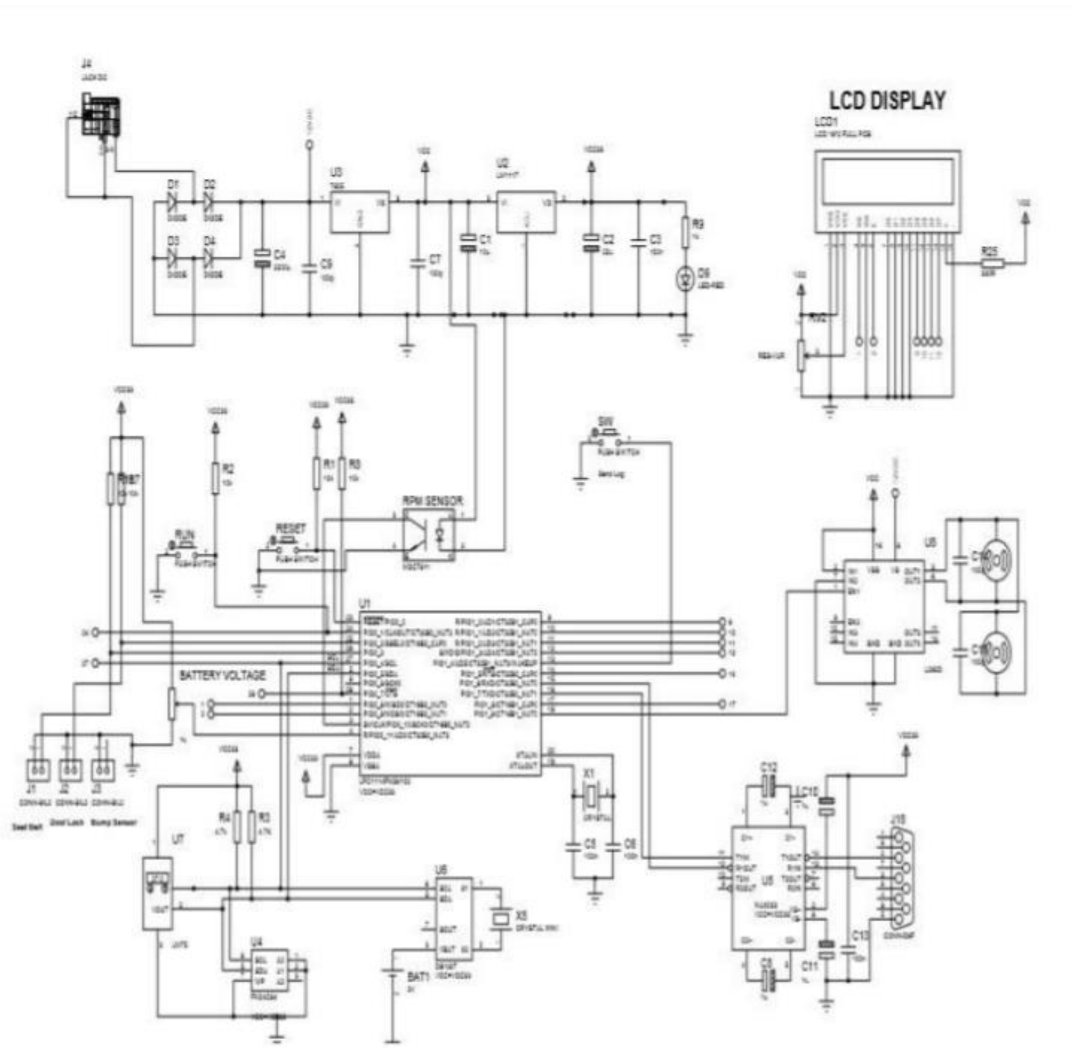
A plane's black box and a car's black box both aid in the investigation of how and why an accident occurred. Plane accidents, on the other hand, are far more difficult to examine. When there is no witness to the collision and each motorist has a different storey of what happened, they may be quite helpful. During an accident investigation, a digital electronics device known as a "car black box" is utilised to capture and preserve information about the vehicle's speed, temperature, vibration, and distance from objects, as well as other vehicle statuses.

In order to save the information, an EEPROM chip is used. As a result, the police and insurance companies may utilise the event data recorder to figure out what actually happened in the collision.

1.1 Proposed Block Diagram



Block diagrams are used in this part to illustrate how we plan to construct the project and its many components. This prototype incorporates sensors for further security. The RISC architecture, on which the ARM processors are based, has allowed for a tiny implementations and very low power consumption.

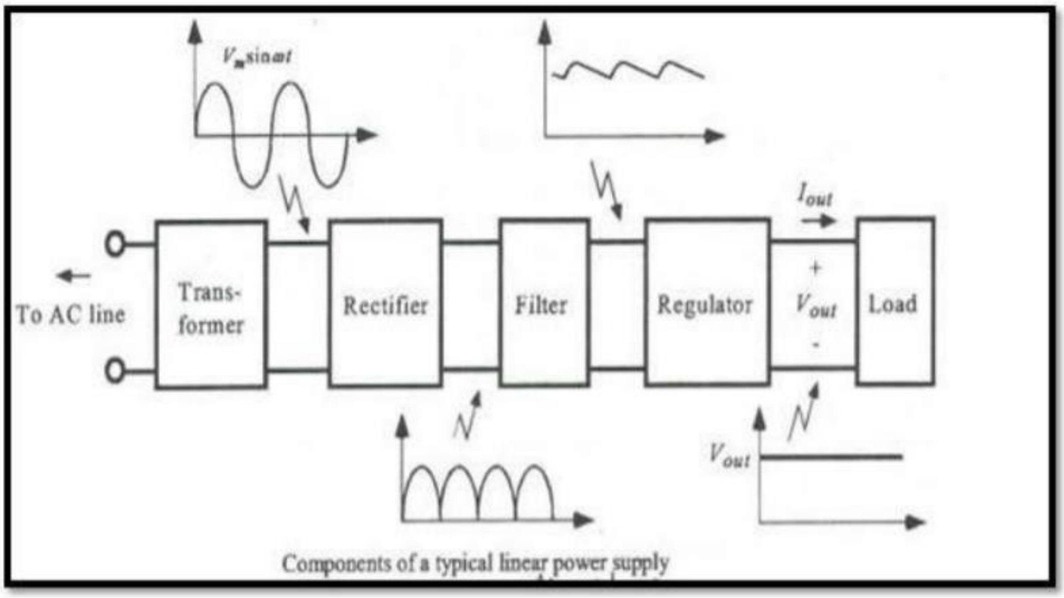


The circuit diagram for the Black Box, which includes the ARM7 CPU and other other components, is shown in this section. As you can see in this figure, all sensors are connected to the CPU. This figure was created using PROTEUS 8.0 software. It has a basic yet effective UI that is straightforward to use.

This block diagram consists of

1.2 POWER SUPPLY:

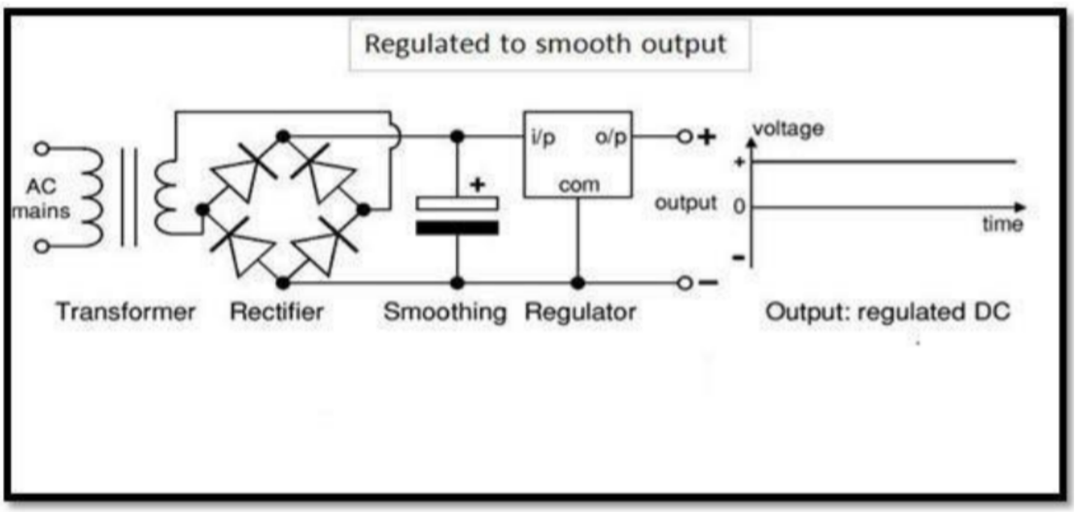
LPC2148 uses 3.3 V power supply in the power supply. A 3.3 V supply is generated using an LM 75. LCD and Motor Driver IC, however, need 5V for their most fundamental functions. As a result, the AC mains supply is reduced to 5 volts. In order to convert 5V into 3.3V, the LM 75 is utilised. Power has been supplied by



Components of a typical linear power supply

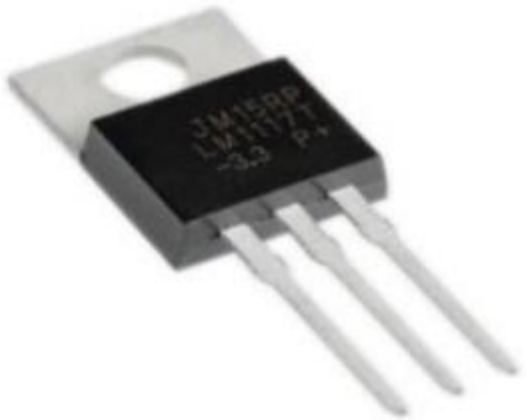
Transformer: To reduce a 230V AC supply to a 9V AC supply, this device is used. It also serves as a means of isolating the circuit from the electrical grid.

Rectifier: “It is used to convert AC supply into DC.”



Filter: "It is used to reduce ripple factor of DC output from rectifier end."

Regulator: "It is used to regulate DC supply output."



1.3 Reset Circuit:

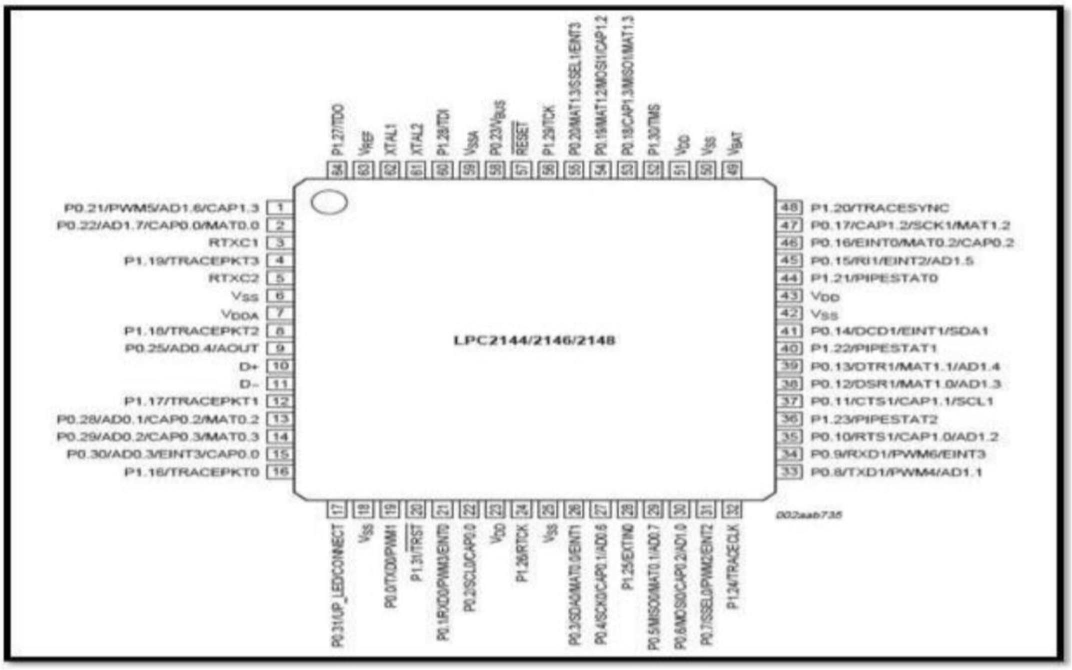
Reset BUTTON: Avoiding programming problems and sometimes manually resetting the system to its startup mode are critical for the system..

1.4 OSCILLATOR:

A crystal is used to generate the oscillations required by the system.

1.5 ARM 7 (LPC2148):

LPC2148 is a common integrated circuit of the ARM7 family. The RISC (reduced instruction set computing) architecture underpins the ARM processor. ARM's instruction set is standardised and always the same length. This processor has two instruction sets: ARM's 32-bit instruction set and Thumb's 16-bit instruction set. In a basic three-stage pipeline, the instructions are fetched, decoded, and executed in that order.



1.6 TEMPERATURE SENSOR:(LM75):

There is a digital over temperature detector included into the LM75 temperature sensor. The LM75's I2C interface allows the host to query it at any moment to get the current temperature. When the programmable temperature limit is exceeded, the open-drain excess temperature output (OS) sinks current. A comparator or interrupt output may be used to control the OS.

TOS is set at +80°C and THYST is set to +75°C during power-up, with the default values for both. Many thermal management and protection applications benefit from the LM75's 3.0V to 5.5V supply voltage range, low supply current, and I2C interface.

1.7 BELT SENSOR

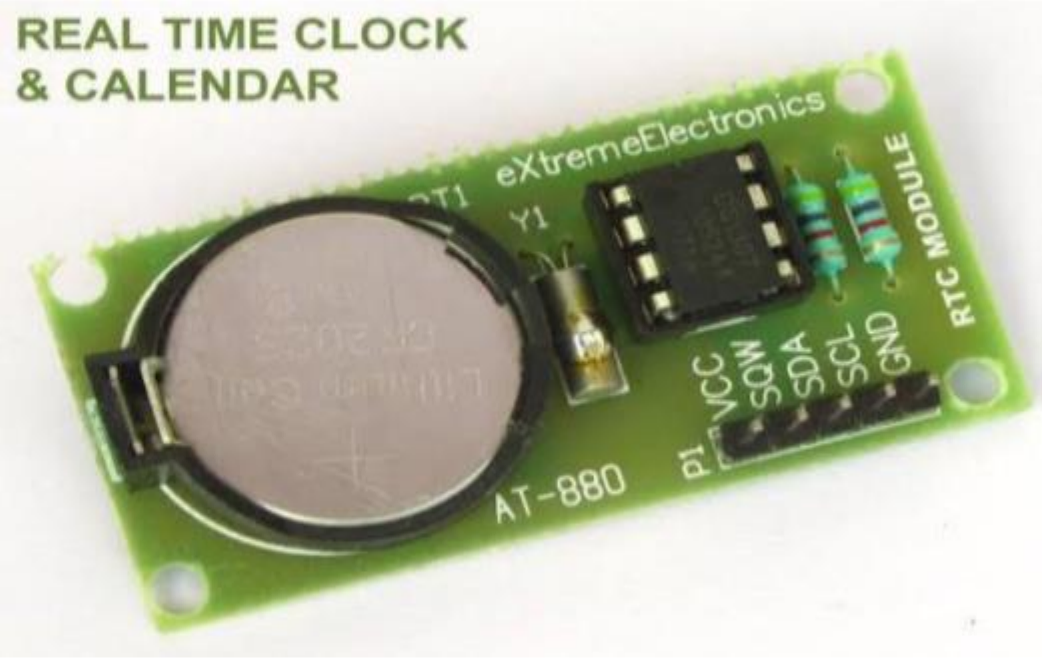
Belt sensors tell whether the seat belts are properly tightened. Audio Jack has been employed as a Belt sensor in our prototype. This is assured by verifying whether the button attached is pushed or not. When driving, a single button is used to determine where the seat belt is in relation to the driver's body. To indicate whether or not the seat belt is being worn, there is a push button on the belt buckle that indicates 'zero' and 'one,' respectively.

1.8 DOOR SENSOR (leaf switch):

Leaf switches serve as door sensors in our prototype, allowing us to determine if the door is closed or open. If this leaf switch is connected, it indicates that the door is closed, and if it is disconnected, it indicates that the door is open, hence the logic 'one' indicates that the switch is connected.

1.9 RTC (REAL TIME CLOCK):

Our clock module's name, Real Time Clock (RTC), suggests its use. Eight pins make up the DS1307 I2C real time clock IC, which is used to keep track of time. All of this information is included in a single clock/calendar.



1.10 OPTOCOUPLER:

We utilised MOC7811 as an opto coupler in our prototype to determine the speed of the wheels on the vehicle. You can see the IR transmitter and the photodiode placed on this opton coupler module When used as a wheel position sensor switch, this is what it looks like. To make it, IR LEDs and photodiodes are attached on opposite sides of a plastic housing. We cut the LED and photo diode circuits and then utilise interrupt to figure out how fast the wheel is spinning.

1.11 RS232:

Microcontrollers communicate with PCs using RS232, a common serial communication technology that uses a variety of communications cables to send data. Connecting the microcontroller to the RS232 port using MAX232.

1.12 DATA RETRIEVING FROM EEPROM:

An EEPROM chip is a kind of computer memory that does not need a power supply to keep data stored in it current. Every sensor information is computed and saved in memory as the incident occurs. In order to understand the cause of the accident, these values are essential. The police and the insurance company may both benefit from the accident data that has been preserved. RS232 connection connects a black box to a personal computer, from whence we acquire the values or data. EEPROMs with I2C compatibility have a bit size of 8192 x 8 bits (M24C64) or 4096 x 8 bits (M40C96) (M24C32). A bidirectional data line plus a clock line make up the I2C serial interface, which is a two-wire design. A 4-bit Device Type Identifier code (1010) is integrated into the devices in line with the requirements of the I2C bus.

2. BACKGROUND

Studies reveal that in-vehicle monitoring considerably reduces dangerous behaviour, particularly among the most risk-prone young drivers. Nevertheless, the decrease in collision or insurance claims rates for young inexperienced drivers has not yet been quantified in the published research. The study shows that when parents see their children's driving, they are more inclined to improve their skills. Only about half of parents, according to some research, really read the remarks.

Studying parents' attitudes has shown that they desire to monitor their children's driving and believe this technology can assist them in doing so. However, parents are worried about the impact of technology on their connection with their children and wish to protect their children's privacy. Data saved online might be hacked or stolen, and parents and young drivers are especially worried about how other organisations could utilise their information.

The results of the attitudinal research indicate possible explanations for why many parents do not obtain input concerning their children's driving, reflecting findings from behavioural studies: As a result, many parents are anxious about having to address their children about their driving habits since they don't understand the data or how to utilise it. As a result, they are seeking advice on how to offer feedback and what to do if the feedback shows risky driving behaviour.

Young drivers may not appreciate the thought of monitoring gadgets, but they are aware that their parents may do so, according to research. There is a growing awareness among millennial drivers that technology may help them avoid making "little mistakes," slow down their inclination to drive too quickly, and resist social pressure. Giving children "objective" statistics rather than parents' judgments on their driving, they believe it will help boost their self-esteem and self-confidence.

However, they believe that the technology does not address essential aspects such as maintaining a safe distance or avoiding risks, and that the feedback has to give solutions rather than merely flag concerns. For them, it is important to have feedback that covers the "actual" safety problems and allows them to explain the facts of what happened. Young drivers fear that a system that needs their parents to use the internet or email would be difficult for them and prohibitively expensive for them.

In the UK, the relationship between a young driver and his or her parents may be quite different because of the country's tiered licencing system, which already imposes certain post-test limitations on new drivers when they first get behind the wheel.

Delivering the Technology

Retro-fitted Device

Now, in-car monitoring does not need the installation of a costly and cumbersome telematics equipment (a "black box") in the vehicle. As a consequence, insurers find it more difficult to provide telematics-based insurance plans, and as a result, these policies tend to be reserved for young drivers who can afford to pay more. Insurers, young drivers, and employers may potentially be put off by the difficulties of installing and perhaps removing the device from the car.

Smartphone App

Using an app on a smartphone instead of installing a real device in a car saves money since it doesn't need the installation of a physical device. applications may also offer information about the driving that was captured by the telematics software itself. As long as the phone is registered to the driver, they may be used to verify their ownership, although this isn't perfect as the phone might be borrowed by another driver.

As a result, using an app to offer the telematics function while the car is in motion may attract some drivers to use their phones for other reasons while driving. By making it plain to the motorist that they should not use their phone while driving and informing them that monitoring equipment would identify and report this if they do, this danger may be reduced to some extent. If a driver feels that their driving is of a lesser level than usual, they may opt to leave their phone at home or turn it on while riding as a passenger in someone else's vehicle so that the app may record the other driver's driving.

As a result, insurers will require a variety of technical solutions to prevent the phone from being used for other reasons and techniques to determine if the car telematics feature is being utilised just on designated routes or when someone else is driving.

Original Equipment

By either mandating it via legislation or mandating it through car manufacturers, the most dependable way to supply telematics technology is to have it incorporated into the vehicles as original equipment at the point of manufacturing (OE). Event Data Recorders (EDRs) will be required on all new automobiles and light trucks sold in the United States starting in September 2013, even though they are now standard equipment on the majority of US vehicles. For a few seconds before to, during, and after a collision, EDRs collect technical data about the car and its occupants, making them fundamentally distinct from the sort of black box being implemented by UK insurers.

Until 2015, all new vehicles sold in Europe will be required to include E-Call (a safety feature that instantly broadcasts the location of the vehicle to emergency services in the event of an accident), but there are no present plans to mandate in-car monitoring as standard equipment in European automobiles. As a result, there is no necessity in the United States for drivers to collect data about their behaviour and performance.

At-Work Drivers

For the first time, businesses are using telematics to monitor their employees' vehicles, presumably mostly vans and trucks, but also in automobiles. Employers may utilise the collected data to develop risk-reduction and efficiency-improving management initiatives, such as shifting routes and timetables, educating drivers, and, if required, instituting disciplinary measures.

Many studies have shown that in-vehicle monitoring may assist employers and at-work drivers minimise their accident rates while driving for work. Some studies have indicated a 20% decrease in accidents for cars equipped with a monitoring system, while others have found a 38% reduction in accidents and an 82% reduction in particular risky driving behaviours. Some fleets saw a decrease in accidents while others had a minor (but statistically significant) rise in accidents as a result of the changes.

Without increasing reaction times, in-vehicle monitoring systems improved driver performance dramatically and consistently in trials in the United States. Without taking into consideration additional savings, such as fewer accidents, the monitoring device saved enough money to pay for itself. It was found that in-vehicle monitoring technology was underutilised in commercial truck and bus safety management in the United States. In addition to driver acceptability, additional hurdles included managing and analysing data as well as ensuring that technology was not just used for negative evaluations and punitive measures.

Telematics has been shown to reduce accidents, accident expenses, vehicle and fuel expenditures, and dangerous driving behaviours in a number of published case studies. This is despite the fact that these case studies have not been published in study papers, and the case studies revealing less favourable findings may not be published.

Feedback

In the study, the most important problem is the significance of feedback on the driving behaviour that is observed by the technology. – Many studies suggest that driving behaviour improves when the driver and/or a third party get feedback, but they give little information regarding the substance or nature of the input.

For example, immediate feedback to the driver in the car and/or retrospective feedback (to the driver and/or a third party, such as a parent or management in the driver's firm) after the voyage has concluded are two common methods of providing feedback. If feedback regarding a child's driving is not being seen by many parents or is being utilised in an unspecific manner, additional study is required in order to discover how to best design, create, and provide feedback that will urge drivers and others to:

View the comments on a regular basis.

The feedback should be interpreted in light of this information.

Utilize the driver's input to help them become a safer driver.

DISCUSSION, ANALYSIS AND FINDINGS

Trucks and public buses across the globe rely on Compression Ignition (CI) engines. In comparison to spark ignition (SI) engines, they have a higher thermal efficiency, better fuel economy, and a longer lifespan [1].

As a result, they contribute to the formation of air pollutants such as Nitrogen Oxides (NOx) and carbon dioxide (CO2), as well as particulate matter (Soot). In this study, we concentrate on diesel soot emissions since they may cause major health concerns, they have a complicated generation and oxidation process that makes modelling soot the most challenging of diesel engine emissions, and soot emissions restrictions are increasing more and stricter [1]. (RDE). Fuel characteristics and fuel mixing, for example, have been linked to soot emissions in prior research [3,4].

The maximum amount of soot that may be created by a vehicle has been steadily lowered over time. Newer emission guidelines limit the size and quantity of particles that may be released into the air (PN). In order to comply with the new Euro 6c regulations, the previous Euro 6b limitations for PN would have to be decreased by a factor of 10. Intelligent engine emission control systems that depend on predictive soot emissions models are one possible approach for complying with tougher emission limits, such as RDE standards. [7] has researched several control systems for diesel engine soot reduction. Model-based engine control, Engine Control Unit (ECU) calibration, and fault diagnostics are all based on engine-out emission modelling [5,8–10]. Internal combustion engine (ICE) sophisticated machine learning (ML) technologies have received greater attention in recent years. Modeling, diagnostics, optimization, and control (ICE) of ML applications have been reviewed in [11].

For diesel engine combustion modelling and emission prediction, physics-based models have been more popular in recent years [12,13]. Because it is computationally costly [14,15], the physics-based technique is not suitable for model-based calibration and real-time model control, even if the comprehensive 3D combustion simulation model may provide physical insight. Soot, HC, and CO emissions are harder to estimate using physical models than NOx emissions are [2,16]. Since soot is one of the most hard to predict, its oxidation and production processes are still a mystery and only thorough physical models are substantially realistic [2]. When examining the most critical aspects of soot oxidation and generation, physical emission models may be an effective tool. Using physical emission models for engine optimization requires a large amount of computer resources. The computing time might be reduced by combining physical models with ML approaches [19].

These models cannot be utilised to regulate emissions in real time since ECUs do not have the computational power to do the necessary calculations. ML approaches may be trained using data-driven or black-box models that employ measurement data directly. These models might be as precise as 3D CFD physical models, but they need substantially less processing time that is sought for the application of model-based controllers in ECUs.. In order to carry out the black-box emission modelling using ML techniques such as: ANN, SVM, RT, ERT, or GPR [20], relevant approaches may be used. Compared to other black-box emission models, the forecast error for soot emissions is often larger [21]. The most often used ML approach for modelling soot emissions is ANN [20], however some research have shown that alternative methods have advantages. SVM and ANN were used in [22] to simulate a diesel engine's black-box emissions using a little quantity of data. Using just a small number of experiments, it was shown that SVM performs better in emission modelling, particularly when it comes to soot emissions. According to our prior research [23], this tendency was also seen.

Because they don't include physical models, black-box models need more calculations than full physical models, although they are less computationally intensive. Because of their lack of experimental data, black-box models are ineffective when it comes to controlling and calibrating engines and analysing the impacts of various engine components. Because it is difficult to gather enough experimental engine data to cover all operating circumstances, black-box models are often not appropriate for investigations that require simulating a large number of instances. In black-box models, extrapolation leads to inaccurate findings. Black-box models are used in gray-box models as a means of addressing these issues. Using a gray-box technique, the advantages of physical modelling and supervised data-driven analysis are combined. Gray-box modelling combines an ML approach with a virtual engine (a 0D or 1D simulation model). This virtual engine's data is used to train the ML technique. A large number of parameters are generated in the virtual engine simulations, some of which are difficult or costly to monitor, such as in-cylinder parameters. Gray-box modelling does not need running the actual engine, making it more suitable for calibration. In general, gray-box models are more accurate than black-box models when it comes to extrapolation and transient analysis.

Using gray-box models, NOx, CO, HC and soot emissions were forecasted in [24]. Nox and soot emission modelling was done in [25] with the use of 1D-CFD and GPR ML methods with defined input feature sets. The study's drawback is the reliance on GPR as the sole data source for the gray-box model. In compared to NOx emissions, the forecast error for soot emissions was shown to be much higher. We've seen this pattern before [16,26].

For a broad spectrum of emissions, gray-box modelling was examined in [16]. Data-driven algorithms with preset input feature sets for varied emission levels were employed in a physical model. ANN approaches were utilised to simulate soot and HC emissions, whereas the GPR method was employed for other pollutants. According to the findings of this research, modelling soot emissions using hybrid and traditional emission modelling techniques is the most challenging task. Although this study employed an advanced ML approach (ANN), there are still other ML methods that may be used for the data-driven component of the research. SVM and ANN algorithms were trained using the specified characteristics for gray- and black-box emission modelling [26]. Another finding from this research was the difficulty in simulating emissions such as soot. In addition, SVM's modelling of soot emissions is more accurate than ANN's. Only physical information of the emissions generation and oxidation process was utilised to choose the fixed input feature sets for emission modelling in both of these studies [16,26].

Because of the gaps in our understanding of soot emissions, it is possible that critical parameters may be overlooked when selecting the input feature set based on physical knowledge. ML feature selection approaches, which were the major focus of our previous work [23], were used to pick the input feature set for a novel gray-box mechanism and black-box emission model for a different diesel engine. There is a novel platform in this study in terms of the number of applicable ML techniques (RT, SVM, BNN and ANN approaches are tried) and a new feature selection procedure that is different from the prior works [16,26]. (LASSO). Improved performance was achieved by using more complex algorithms (such as Bayesian and grid search) for the optimization of the hyperparameters of the machine learning techniques (ML). An approach for picking input characteristics, such as a systematic feature selection technique, is shown to increase model prediction accuracy in this research.

An unsupervised clustering approach may be used to classify data based on how similar it is to a given group. It is possible to employ clustering as a pre- or post-processing method. It is possible to categorise incoming data based on similarities using clustering as a pre-processing method. As a result, each group's data will be treated as a distinct set and examined as such. K-means clustering is a well-known ML technique for clustering. A clustering method known as K-means is used in [27] to classify automobiles into groups according on their emission output. Each cluster was tested using a variety of machine learning techniques, and the ones that performed best were chosen. Research suggests that a better prediction accuracy may be achieved by pre-clustering data. An engine's combustion events were also classified using this method [28]. When the output of a simulation is broken down into separate groups, clustering may be employed as an effective post-processing technique. A diesel engine's soot production within the combustion chamber was calculated using a CFD simulation [29]. The K-means clustering technique was then used to divide the combustor into separate zones based on the rate of soot production in the engine combustor. Soot formation analyses and methods for reducing soot generation in high soot regions were made easier by the separation of low soot areas from high soot areas.

An algorithm called K-means is used to categorise diverse approaches and feature sets into groups depending on their accuracy, complexity, time-consumingness, etc. This allows for a more methodical selection of algorithms and feature sets. In the end, the goal is to choose the most effective methodologies and feature sets. To ensure that the comparison is fair, all techniques utilise the identical experimental data as inputs. After categorising multiple feature sets and regression techniques, a K-means clustering algorithm is utilised to recommend the best solutions for distinct applications.

The following are the most significant research gaps and the paper's new contributions to the field of soot emissions modelling:

There is a lack of published data on soot emissions for "full" speed-load maps from medium-duty diesel compression ignition engines, even though some papers have investigated the effects of various parameters on the emission production of diesel engines, for example, the effect of fuel properties [30]. In order to correctly detect soot emissions, it requires extensive calibration procedures for emission analyzers, which are expensive and time-consuming. Soot emission data for a 4.5 L 4-cylinder diesel engine's entire speed-load map is measured in this study. This dataset serves as a standard against which the various modelling approaches in this research may be compared.

• The input feature set has a significant impact on the performance of ML algorithms. It is typical practise in emission modelling using ML approaches to choose the input feature set mostly based on physical information. It is possible to overlook important aspects of a situation owing to a lack of information or misinterpretation of physical relationships. Choosing a subset based on physical information is particularly challenging in gray-box emission modelling since the model produces so many characteristics. There are a variety of input feature sets to choose from in this study, including ML feature selection and physical knowledge.

• SVM, ANN, and GPR, together with a fixed input feature set, were previously employed in previous works to predict soot emissions using traditional machine learning approaches. For soot emission modelling, there is a paucity of systematic research that evaluate various ML approaches and feature sets. A total of 40 soot emission models are created in this study using eight distinct ML algorithms and five different feature sets.

Previous soot emission modelling studies have not included post-processing approaches for analysing the data and method selection. An unsupervised machine learning algorithm is utilised to analyse and compare several engine soot emission models in this article. The best soot emission models are selected using two K-means clustering techniques that act as filters. Other engine modelling research should benefit from this technique as well.

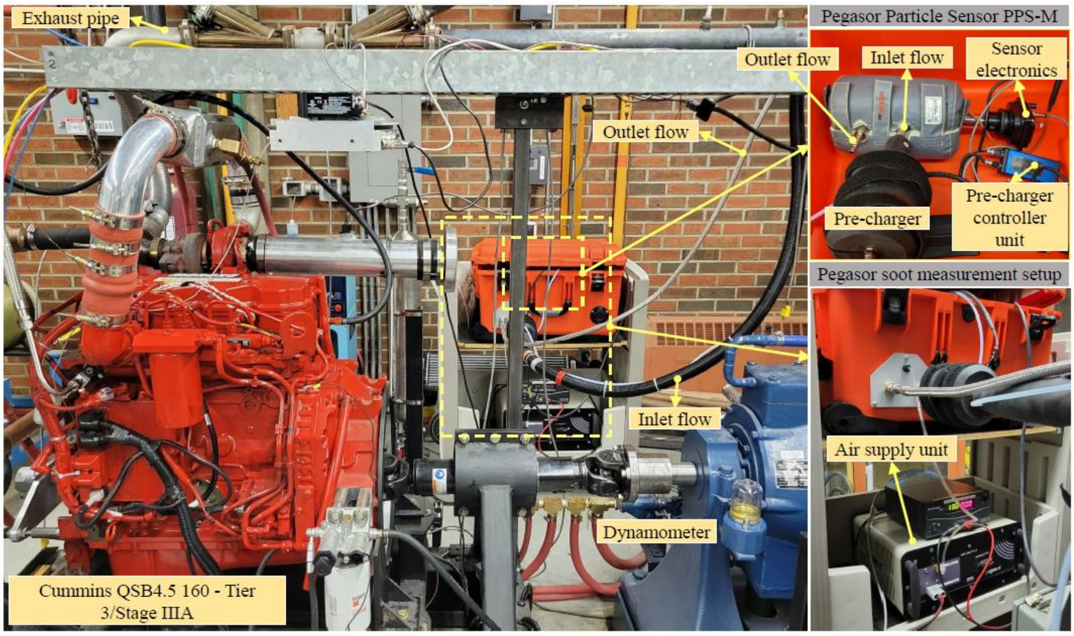
Sections are used to organise the document. The engine's physical model and experimental setup are first discussed. There is also a discussion of the black box and grey box versions here. The black-box and gray-box models each have two feature sets, whereas the gray-box model has three feature sets. Lastly, the ML approaches that are used in pre-processing, processing, and post-processing are briefly discussed. Using a K-means clustering algorithm, results from various methodologies and feature sets may be compared and evaluated in terms of accuracy, complexity, and timeliness. The last portion of the paper discusses the results.

3.1 Experimental Setup

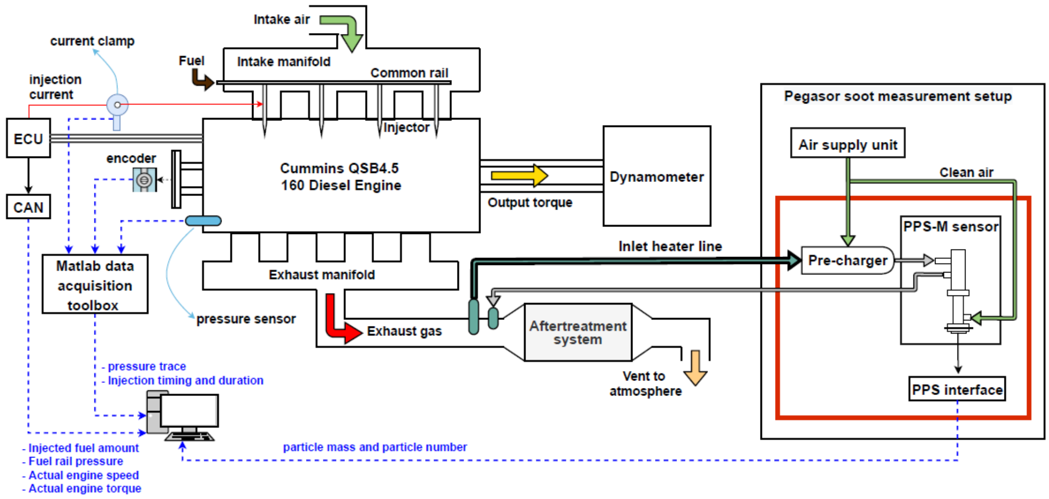
To gather data on soot emissions, a 4.5-liter medium-duty Cummins diesel engine was employed. Table 1 lists the specs for the Cummins QSB4.5 160 diesel engine. Tests on this engine are being carried out at University of Alberta's internal combustion engine facility, and soot emission data collecting is presented in Figure 1. In this configuration, the engine ECU records intake air pressure, engine speed, load, injected fuel quantity, and fuel rail pressure. For this purpose, the Cummins INLINE6 interface and INSITE Pro Cummins are employed to communicate with the ECU. A Pico current clamp and a Kistler piezoelectric pressure sensor are used to detect the in-cylinder pressure and the command signal from the injector.

Table 1. Engine specifications.

Parameter	Value
Engine type	In-Line, 4-Cylinder
Displacement	4.5 L
Bore × Stroke	102 mm × 120 mm
Peak torque	624 N.m @ 1500 rpm
Peak power	123 kW @ 2000 rpm
Aspiration	Turbocharged and Charge Air Cooled
Certification Level	Tier 3/Stage IIIA



(a)



(b)

Figure 1. Diesel engine with soot measurement experimental setup. (**a**) Experimental setup. (**b**) Schematic of experimental setup.

A Pegasor Particle Sensor (PPS-M) is used to monitor soot emissions. Figure 1b depicts the concept for the soot measuring system, which uses an intake heater line to send engine exhaust gas to the pre-charger. For soot measurement, the pre-charger is employed to prevent any charge-related issues Soot measurement requires a pre-charger because of the possibility of highly charged tiny particles in exhaust due to recent advancements in emission technology. Non-radioactive, self-heating Pegasor Pre-Charger with negative diffusion. Larger charged particles may be charged with known negative charges using Pegasor's built-in ion trap. PPS-M has a sampling rate of 100 Hz and a sensor to noise ratio of 100 dB. (SNR). [0.001 to 290] mg/m3 [mg/cm3] is the range of particle sizes this sensor can detect. Table 2 lists the primary PPS-M sensor specifications.

Table 2. The PPS-M sensor specifications.

Parameter	Value
Sensor temperature	200 °C
Extracted sample temperature	−40 up to 850 °C
Dilution	No need
Time response	0.2 s
Measured particle size range	10 nm and up
Trap voltage	60 V (10 nm lower cut) 400 V (23 nm lower cut, default) 2 kV (90 nm lower cut)
Particle number range	300 up to 10^9 1/cm^3
Particle mass range	10^{-3} up to 300 mg/m^3
Sample pressure	−20 kPa to +100 kPa
Clean air/Nitrogen supply	10 LPM @ 0.15 MPa
Operating voltage	24 V
Power consumption	6 W

At 219 engine steady state working settings, the diesel engine was tested at all speeds and load levels. As shown in Figure 2, raw soot emission data is coloured according to engine speed (x-axis) and load (y-axis). Black dots indicate experimental points. Because it is intended for fixed use, this engine's working conditions are rather restricted. Figure 2's 219 data points cover the vast majority of operational situations, as seen in the figure. 220 data points may not be enough for highway truck applications owing to the variety of driving cycles, since more than 900 data points have been employed in the literature for this application [26].

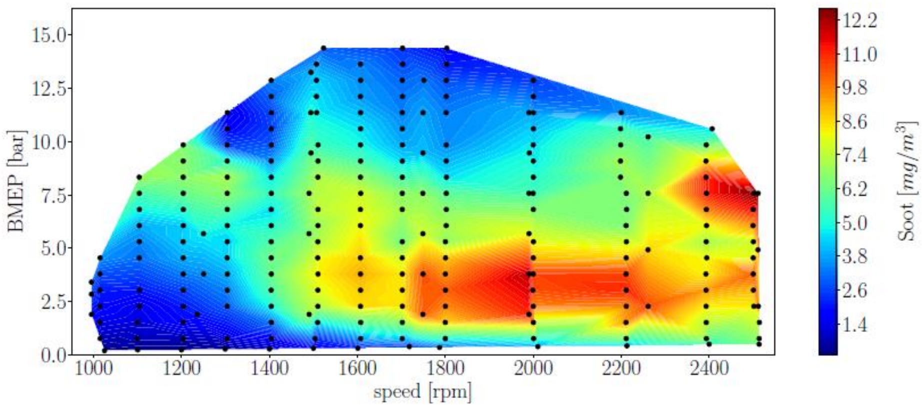
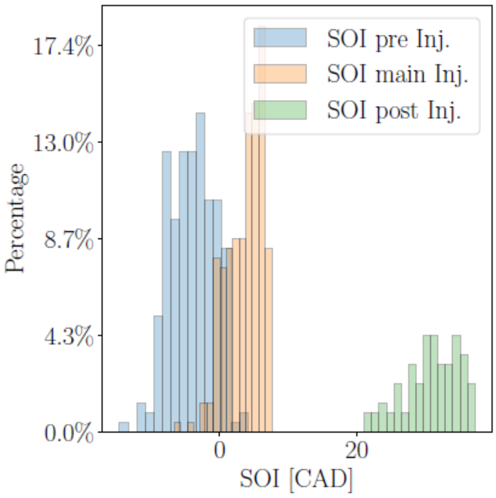
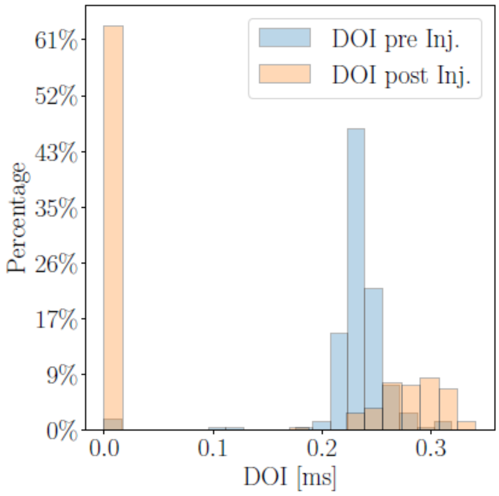


Figure 2. Engine-out soot measurements over speed and Break Mean Effective Pressure (BMEP).

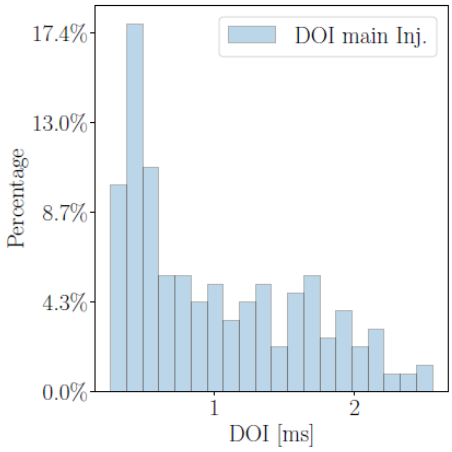
Figure 3 shows a histogram of the key characteristics of the diesel engine that are relevant to both the performance and the modelling of soot emissions. Figure 3b shows that the third injection pulse is active in 39% of the data we experimentally obtained for this diesel engine. Each cycle's total amount of injected fuel is shown in Figure 3a–d along with the start and end times for all injection pulses. Figure 3e illustrates the influence of common rail pressure on soot emission modelling. Most of the data is gathered in the 700-1100 bar fuel rail pressure range. Figure 3f–g illustrates the air route, intake manifold pressure, and air-fuel equivalency ratio (l). Additionally, output torque and engine speed are presented in Figure 3h–i. These histograms show that the data gathered from trials covers a large portion of the engine's operating circumstances.


SOI pre Inj.
SOI main Inj.
SOI post Inj.
17.4%
13.0%
8.7%
4.3%
0.0%
Percentage
0
20
SOI [CAD]

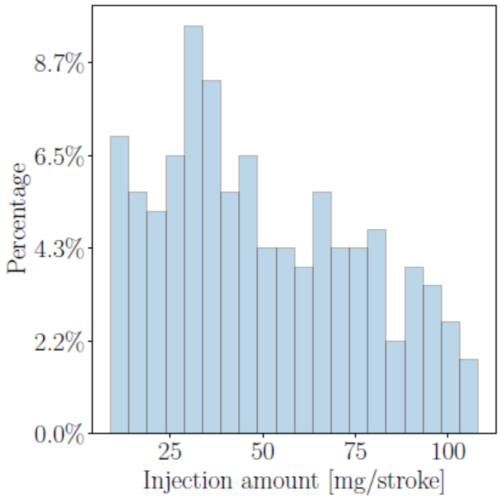
(a)


DOI pre Inj.
DOI post Inj.
61%
52%
43%
35%
26%
17%
9%
0%
Percentage
0.0
0.1
0.2
0.3
DOI [ms]

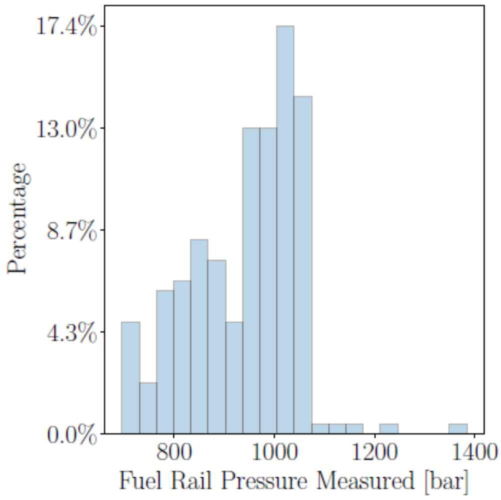
(b)


DOI main Inj.
17.4%
13.0%
8.7%
4.3%
0.0%
Percentage
1
2
DOI [ms]

(c)


8.7%
6.5%
4.3%
2.2%
0.0%
Percentage
25
50
75
100
Injection amount [mg/stroke]

(d)


17.4%
13.0%
8.7%
4.3%
0.0%
Percentage
800
1000
1200
1400
Fuel Rail Pressure Measured [bar]

(e)

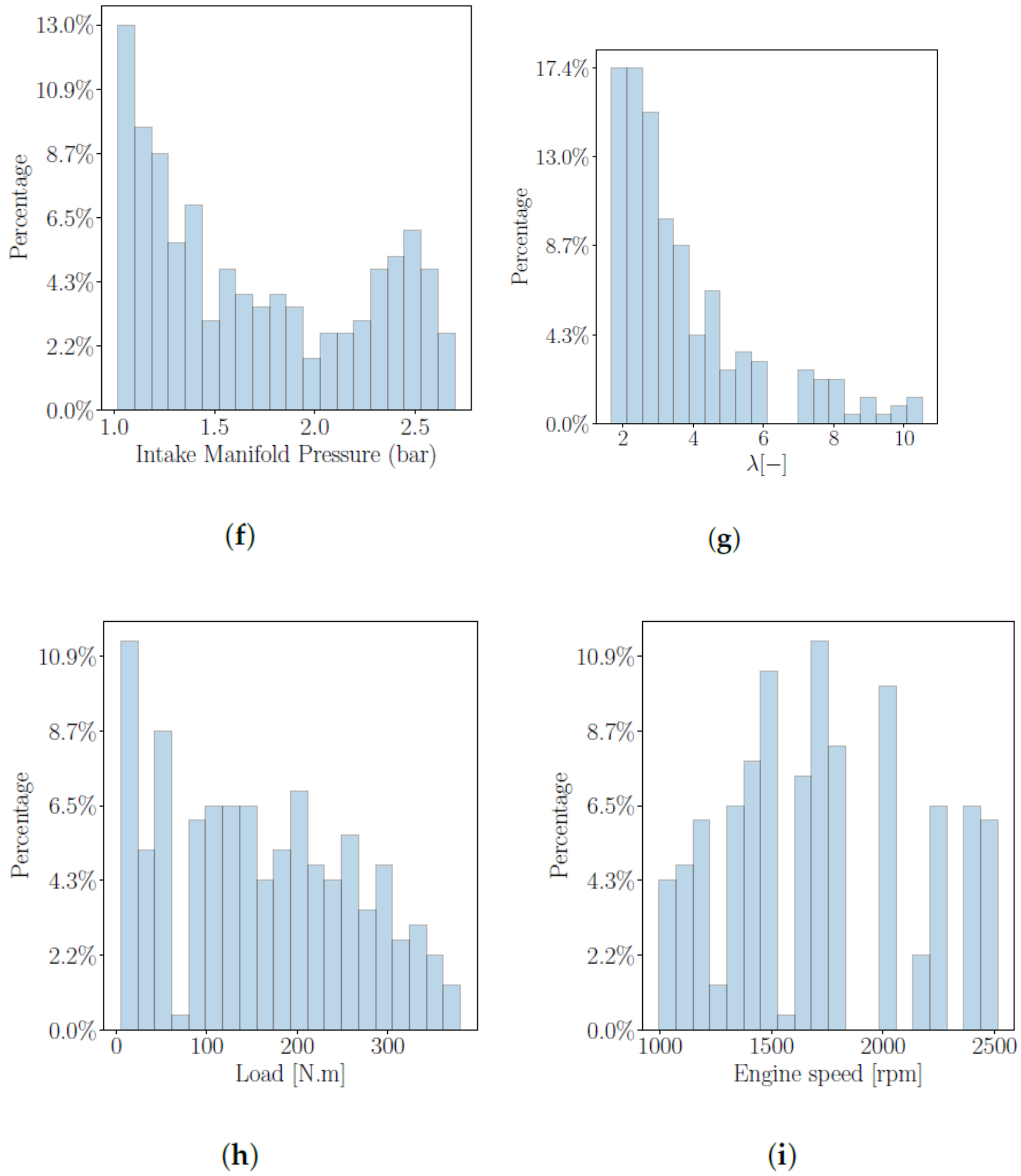


Figure 3. Histogram of diesel engine main experimental features. (**a**) Start of Injection (SOI). (**b**) Duration of Injection (DOI). (**c**) Duration of main injection. (**d**) Injected fuel amount per cycle. (**e**) Fuel rail pressure. (**f**) Intake manifold pressure. (**g**) Air-fuel equivalence ratio (λ). (**h**) Output torque (load). (**i**) Engine Speed.

3.2 Gray-Box and Black-Box Models

This section describes the physical model, the black box, and the grey box. The GT-Power physics-based model was the initial step in building physical and gray-box models. An engine modelling programme, GT power, is available to the general public for purchase. The G T power programme is used to mimic the complicated combustion processes of the diesel engine, which includes various chemical and physical sub-models. Because it may be utilised with a multi-injection diesel combustion engine, DIpulse is the combustion model of choice.

The physical soot model is based on the Hiroyasu model [32]. Using just 8% of the data, the model is calibrated. For multi-objective Pareto optimization, the search method used in the calibration phase is Genetic Algorithm (GA) NSGA-III [33]. Because it can investigate a wide range of design options, GA is the best solution for a wide range of issues [33]. The population size and the number of generations are the two most important inputs for GA. Two separate general analytic models (GAs) are utilised to calibrate the combustion model and the soot model. Since combustion models are far more complicated and include more variables than soot models, there are 16 generations of the population for each algorithm, however there are only 10 generations for each method for soot model calibration. Figure 4 demonstrates how the GA-based technique is used to compute the soot model and combustion model multipliers. Soot emissions and in-cylinder pressure traces were taken into consideration for select optimization areas by the GAs based on their findings. The multipliers for the combustion model include the entertainment rate multiplier, the ignition delay multiplier, the premixed combustion rate multiplier, and the diffusion combustion rate multiplier. The soot model also includes two multipliers: one for the creation of soot, and another for the burning up of that soot. The best multipliers are calculated by minimising the difference between the experimental and simulation in-cylinder pressure trace and soot emission data. Soot emissions and in-cylinder pressure were calibrated individually using two distinct GAs in this example.

The amount and timing of injection pulses have a significant impact on diesel engine soot emissions [34]. The Cummins diesel engine injection system has three primary pulses: Pulse I is pre-injection, Pulse II is the main injection, and Pulse III is post-injection, which only occurs in a few load zones. To reduce soot emissions, post injection plays a key role in enhancing the soot emissions burn rate.

It is displayed in Figure 5 as a function of crank angle (CAD) the in-cylinder pressure trace for various load and speed situations. Among the optimization points utilised for model calibration, only examples I (136 [N.m] in 1200 [rpm]), IV (271-271 [N.m] in 1800 [rpm]), and VI (353 [N.m] in 2400 [rpm] are chosen (see Figure 4). Figure 6 shows the results of the validation tests for the crank angle at which 50% of the heat is emitted (CA50), NOx, intake manifold pressure, and maximum in-cylinder pressure. The physical model's accuracy is shown by its CA50 and maximum in-cylinder pressure errors of roughly 2 CAD and 6 percent, respectively.

Feature selection is the process of picking the most significant features from a large feature collection (FS). By reducing the size of the input feature set, FS enhances the performance of ML methods. Figure 4 depicts the FS process in a simplified form. In order to model soot emissions, this research makes use of five different feature sets. A mix of physical insight and the LASSO feature selection method is employed for FS in this study.. Expert knowledge is used to pick the most important features in physical insight feature selection whereas the more systematic method of LASSO feature selection is used to select characteristics independent of previous knowledge about the system.

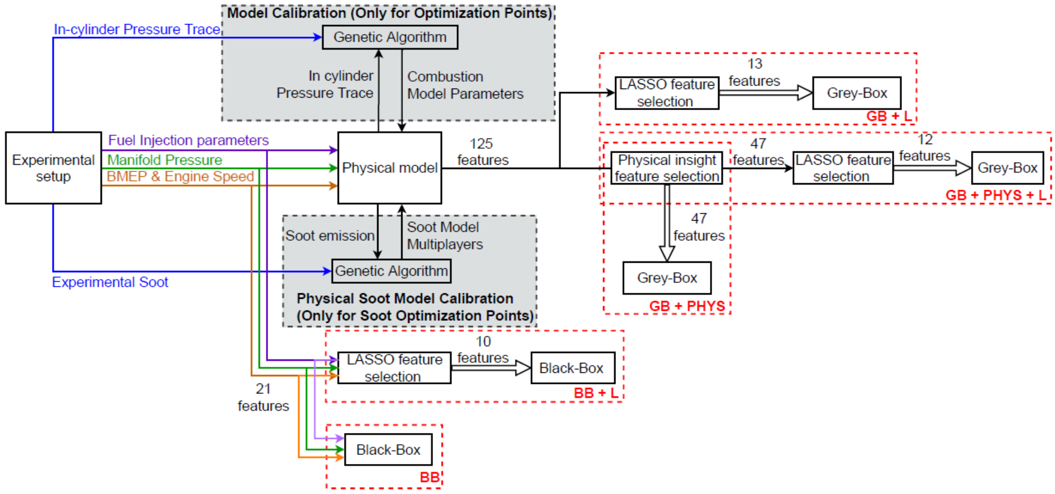


Figure 4. Physical model calibration and feature selection process.

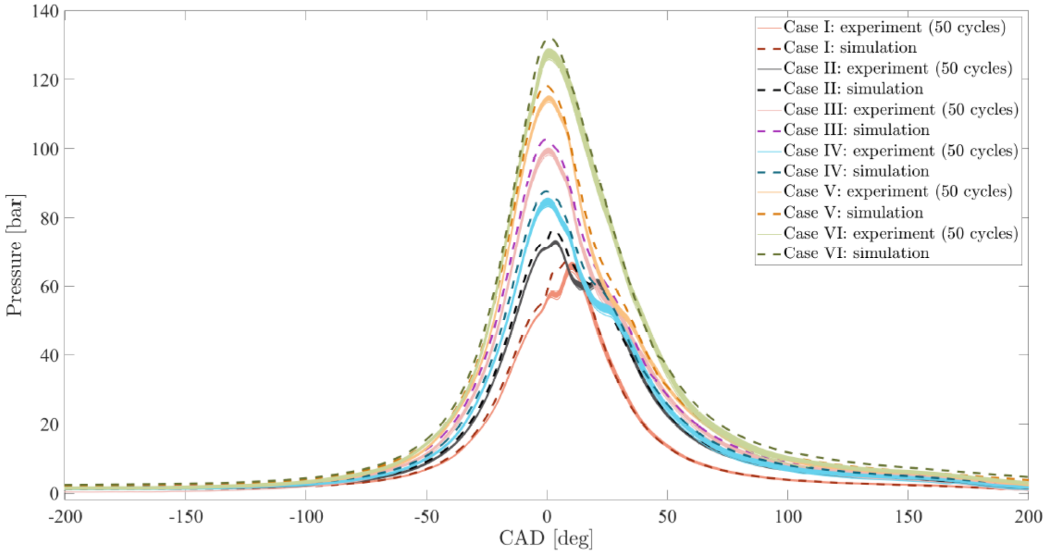


Figure 5. Physical–based model validation for six operating points. (Case I: 136 [N.m] in 1200 [rpm], Case II: 271 [N.m] in 1600 [rpm], Case III: 271 [N.m] in 1400 [rpm], Case IV: 271 [N.m] in 1800 [rpm], Case V: 271 [N.m] in 2000 [rpm], and Case VI: 353 [N.m] in 2400 [rpm]).

Only experimental data are included in the two black-box feature sets: one without any feature selection technique (BB), and the other using LASSO (BB + L). GB + PHYS, GB + L, and GB + PHYS + L are the gray-box feature sets. Only physical understanding into soot oxidation and production processes is used to choose data-driven characteristics in GB + PHYS. The LASSO feature selection technique is used to pick the parameters in GB + L. Finally, GB + PHYS + L applies the LASSO feature selection approach after selecting the most significant characteristics with the help of physical understanding first. Figure 4 summarises the number of characteristics for each of the five approaches and phases.

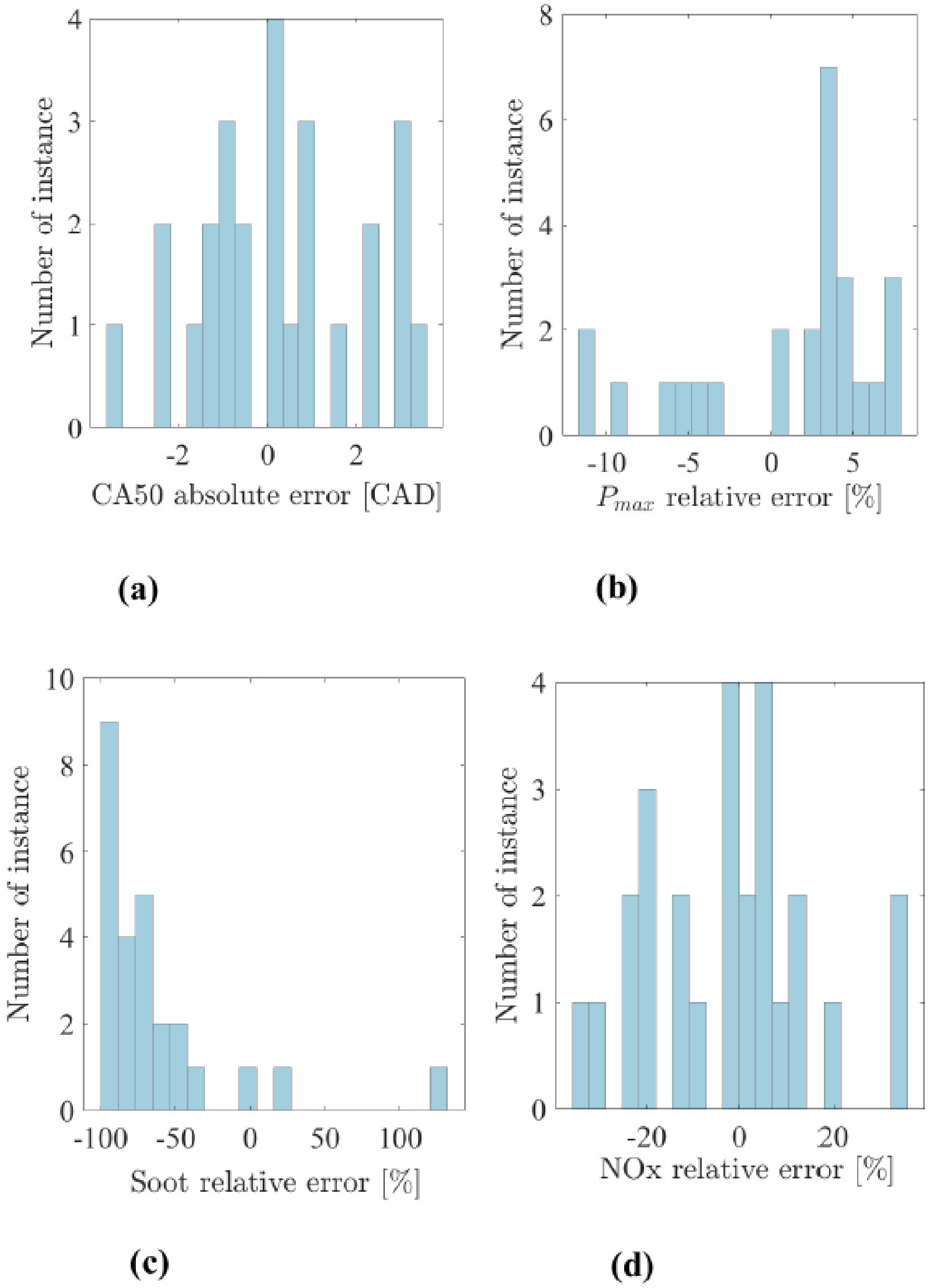


Figure 6. Histogram of error between physical–based model and experimental data. (**a**) CA50 absolute error [CAD], (**b**) Maximum In-cylinder pressure (P_{max}) relative error [%], (**c**) Soot emission relative error [%], (**d**) NOx emission relative error [%].

A black-box and gray-box soot modelling diagram is shown in Figure 7. As can be seen, the virtual engine makes advantage of the experimental injection time. BMEP, intake manifold pressure, start of injection (SOI), fuel rail pressure, and engine speed are all included in the gray-box and black-box models, respectively, as illustrated in Figure 4. Models and feature sets are selected using the K-means clustering approach based on mistakes and timing (testing and training times). There are two different K-means clustering techniques used (the first filter and the second filter). In the first filter, low-quality feature sets and models are eliminated, while the second filter picks the optimum ML technique and feature sets in terms of accuracy and training and prediction costs for diverse applications. Twelve different soot models have been selected, and the results and debate will be discussed in more detail below.

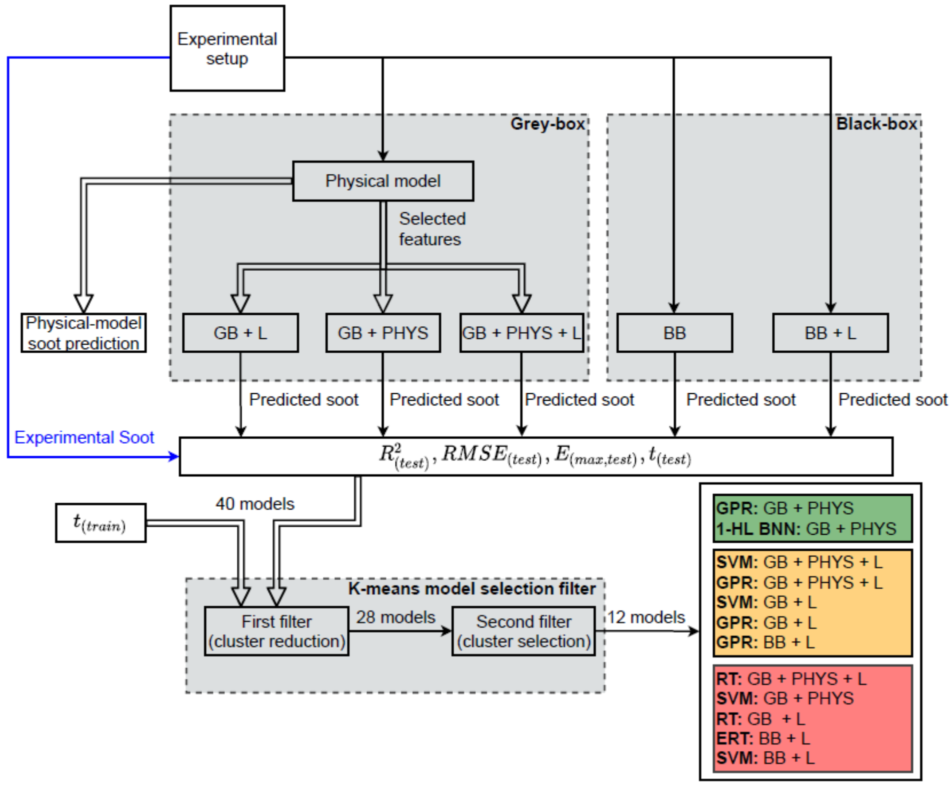


Figure 7. Overview of the gray-box (GB) and black-box (BB) soot emissions model selection process by K-means clustering algorithm.

3.3 Machine Learning Methods

Pre-processing, modelling, and post-processing all make use of machine learning methods in this work.

3.3.1 Pre-Processing: Feature Selection

For both black-box and gray-box models, the LASSO feature selection approach is used to obtain the most effective soot prediction parameters. In order to increase the model's prediction accuracy, LASSO uses feature selection and regularisation. Model coefficients, which are used to forecast the outcome, are computed by minimising the following cost function:

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 + \lambda \sum_{i=1}^{m} |\theta_i| \qquad (1)$$

“where m is the number of training data points, åmi=1 jqij is the L1 regularization and l is regularization variable. Adding L1 regularization leads to driving the weights down to exactly zero (produces sparsity in the solution) and results in performing a systematic feature selection [36]. This sparsity depends on l, which is calculated in the cross-validation process in the current study.”

3.3.2 Regression Models

"The five well-known supervised learning regression algorithms are employed: Regression Trees (RT), Ensemble of the Regression Trees (ERT), Gaussian Process Regression (GPR), Support Vector Machine (SVM), and Neural Network (NN). These are used to train both the black and gray-box soot models.

A data-driven regression model can be generalized to fitting a parameterized model, ˆ y = hq(xi), for given training set Dtrain = (xi, yi) such that ˆ y converges to yi subject to given constrains. In this problem, xi is input feature, yi is the measured output, and q is the parameters set. The parameters set can be calculated by solving following optimization problem."

$$\begin{array}{ll} \min\limits_{\theta} & J(\theta) \\ \text{s.t.} & \phi(\theta) \end{array} \tag{2}$$

"where f(q) is constraints function and J(Q) is a cost function which is defined as"

$$J(\Theta) = \bar{J}(\Theta) + \lambda L(\Theta) \tag{3}$$

where "J(Q) is defined based on error ei(Q) = hq(xi) yi to minimize prediction error while regularization term, L(Q), is added to regulate parameters, Q. In general, L(Q) is L1 or L2 loss function for regularization purpose. For LASSO regression, L1 loss function is used while in other regression methods such as Ridge, SVM, and ANN L2 loss function is used. L2 loss function is defined as:"

$$L_2(\Theta) = \sum_{i=1}^{m} (\theta)^2 \tag{4}$$

"The regulatory parameter or penalized variable, l, produces a trade-off between the smoothness of the model and the training error tolerance minimization [36]."

Table 3. Training and optimization of ML-based model hyperparameters. In this table MSL is minimum samples leaf for regression tree and ensembles trees methods, λ is the regularization parameter and ϵ is the maximum tolerable deviation for support vector machione method, and σ_l is the length scale of Gaussian process regression method.

<table>
<tr><th>Method</th><th>Opt. Method</th><th>Opt. Hyperparameters</th><th>Model Type</th><th>Opt. Model Configuration</th></tr>
<tr><td>RT</td><td>Bayesian</td><td>Min samples leaf (MSL)</td><td>BB
BB + L
GB + L
GB + PHYS
GB + PHYS + L</td><td>MSL = 13
MSL = 1
MSL = 5
MSL = 5
MSL = 5</td></tr>
<tr><td>ERT</td><td>Bayesian</td><td>Ensemble method, min samples leaf, and number of learners</td><td>BB
BB + L
GB + L
GB + PHYS
GB + PHYS + L</td><td>Boosting, 75 Learners, and MSL = 2
Boosting, 28 Learners, and MSL = 4
Boosting, 35 Learners, and MSL = 5
Boosting, 488 Learners, and MSL = 47
Boosting, 487 Learners, and MSL = 2</td></tr>
<tr><td>SVM</td><td>Bayesian</td><td>Kernel function λ and ϵ</td><td>BB
BB + L
GB + L
GB + PHYS
GB + PHYS + L</td><td>Cubic, $\lambda = 0.96$, $\epsilon = 0.010$
Quadratic, $\lambda = 0.77$, $\epsilon = 0.330$
Gaussian, $\lambda = 9.59$, $\epsilon = 0.004$
Quadratic, $\lambda = 3.49$, $\epsilon = 0.003$
Cube, $\lambda = 5.79$, $\epsilon = 0.009$</td></tr>
<tr><td>GPR</td><td>Bayesian</td><td>Kernel function, initial value for the noise standard deviation (σ)</td><td>BB
BB + L
GB + L
GB + PHYS
GB + PHYS + L</td><td>Rational quadratic, $\sigma = 12.68$
Rational quadratic, $\sigma = 0.0005$
Matérn 5/2, $\sigma = 0.0001$
Matérn 5/2, $\sigma = 0.0001$
Matérn 5/2, $\sigma = 2.996$</td></tr>
<tr><td>1-HL ANN</td><td>Grid search</td><td>Number of neurons in each layer</td><td>BB
BB + L
GB + L
GB + PHYS
GB + PHYS + L</td><td>Network conf.: [25]
Network conf.: [19]
Network conf.: [4]
Network conf.: [4]
Network conf.: [19]</td></tr>
<tr><td>2-HL ANN</td><td>Grid search</td><td>Number of neurons in each layer</td><td>BB
BB + L
GB + L
GB + PHYS
GB + PHYS + L</td><td>Network conf.: [7, 25]
Network conf.: [25, 31]
Network conf.: [4, 13]
Network conf.: [7,13]
Network conf.: [16, 19]</td></tr>
<tr><td>1-HL BNN</td><td>Grid search</td><td>Number of neurons in each layer</td><td>BB
BB + L
GB + L
GB + PHYS
GB + PHYS + L</td><td>Network conf.: [7]
Network conf.: [31]
Network conf.: [31]
Network conf.: [13]
Network conf.: [25]</td></tr>
<tr><td>2-HL BNN</td><td>Grid search</td><td>Number of neurons in each layer</td><td>BB
BB + L
GB + L
GB + PHYS
GB + PHYS + L</td><td>Network conf.: [7, 28]
Network conf.: [16, 13]
Network conf.: [10, 22]
Network conf.: [22, 22]
Network conf.: [10, 19]</td></tr>
</table>

CONCLUSION

In the beginning, it seems that the model's outcomes are satisfactory. The oxygen buffer appears to work well for the model in the majority of circumstances. This may be the most difficult situation to solve for the model, but at higher switching amplitudes, the model seems to match both test scenarios rather well. To increase performance at low amplitudes, one option is to tune the model, which is obviously possible. Weaknesses in the model's low-amplitude behaviour mean that even while the model says we shouldn't emit any emissions at all, we may nevertheless leak them if we used it in a control-oriented way. However, the model has a built-in reset to prevent this from happening. Even though this hasn't been documented, it was tested in a simulated setting and returned satisfactory results. The reset function, on the other hand, must be calibrated to the right value for the present sensor being used.

We can observe from the model what occurs during traditional bang bang control when just the first portion of the catalyst (slice one to two) is active. An improvement in control of the catalyst would suggest that the catalyst is underutilised. For example, the catalyst's full capacity might be used when utilising the control technique outlined in 4.1. Since this is a rather simple control method, it is interesting to note how effectively it works, despite its lack of sophistication. However, it has been widely employed since the introduction of three-way catalytic converters in petrol vehicles. However, despite the catalyst's impressive efficiency, the model suggests that more powerful controllers may be able to substantially enhance the system's performance.

As a result of the thesis, there is a universal agreement that complexity imposes limitations. Computational power is required to handle complicated models that have many states and responses, restricting the use of sophisticated control techniques and complex controllers. In 2019, sophisticated controllers would need a significant amount of processing power, which would restrict the model's ability to be as advanced as possible. For the sake of simplicity, let's say that an advanced model requires an advanced controller whereas a basic model does not. Because basic models can be handled by a simple controller, the usage of a complex controller like an optimising MPC is unnecessary and rather stupid. As a result, this thesis used a sophisticated model and a basic controller. This variant may be used in conjunction with more complex controllers in the future as car ECU performance improves.

REFERENCES

[1] Theophil S Auckenthaler. Modelling and control of three-way catalytic converters. ETH Zurich, 2005.

[2] Lars Eriksson and Lars Nielsen. Modeling and control of engines and drivelines. John Wiley & Sons, 2014.

[3] John B. Heywood. Internal Combustion Engine Fundamentals, Second Edition. McGrawHill Education, 2018.

[4] Karthik Ramanathan and Chander Shekhar Sharma. Kinetic parameters estimation for three way catalyst modeling. Industrial & Engineering Chemistry Research, 50(17):9960– 9979, 2011.

[5] Michail I Soumelidis, Richard K Stobart, and Richard A Jackson. A nonlinear dynamic model for three-way catalyst control and diagnosis. SAE transactions, pages 764–775, 2004.

[6] Theophil S Auckenthaler, Christopher H Onder, and Hans P Geering. Online estimation of the oxygen storage level of a three-way catalyst. Technical report, SAE Technical Paper, 2004.

[7] Christopher H. Onder Theophil S. Auckenthaler and Hans P. Geering. Modelling of a solid-electrolyte oxygen sensor. 01 2002.

[8] James C Peyton Jones. Modeling combined catalyst oxygen storage and reversible deactivation dynamics for improved emissions prediction. Technical report, SAE Technical Paper, 2003.

[9] Mordecai Shelef and Robert W McCabe. Twenty-five years after introduction of automotive catalysts: what next? Catalysis today, 62(1):35–50, 2000.

[10] Pankaj Kumar, Imad Makki, James Kerns, Karolos Grigoriadis, Matthew Franchek, and Vemuri Balakotaiah. A low-dimensional model for describing the oxygen storage capacity and transient behavior of a three-way catalytic converter. Chemical engineering science, 73:373–387, 2012.

[11] Masayuki Kato, Takaki Matsumoto, Shinichiro Otsuka, Hirosuke Okubo, Yoshiaki Matsuzono, and Shogo Konya. Numerical modeling of automotive exhaust catalysts. Technical report, SAE Technical Paper, 2011.

[12] James C Peyton Jones, J Brian Roberts, Pierre Bernard, and Richard A Jackson. A simplified model for the dynamics of a three-way catalytic converter. Technical report, SAE Technical Paper, 2000.

[13] F_ Aimard, S Li, and M Sorine. Mathematical modeling of automotive three-way catalytic converters with oxygen storage capacity. Control Engineering Practice, 4(8):1119–1124, 1996.

[14] Romit Godi and Simona Onori. Reduced order model design for three way catalytic converter temperature dynamics. pages 886–891, 2017.

[15] Olov Holmer and Lars Eriksson. Modelling and validation of hybrid heavy duty vehicles with exhaust aftertreatment systems. (138):304–316, 2017.

[16] GC Koltsakis, PA Konstantinidis, and AM Stamatelos. Development and application range of mathematical models for 3-way catalytic converters. Applied Catalysis B: Environmental, 12(2-3):161–191, 1997.

[17] Pankaj Kumar and Imad Makki. Model based control of a three-way catalytic converter based on the oxygen storage level of the catalyst. Technical report, SAE Technical Paper, 2017.

[18] Clifford N Montreuil, Scott C Williams, and Andrew A Adamczyk. Modeling current generation catalytic converters: Laboratory experiments and kinetic parameter optimizationsteady state kinetics. Technical report, SAE Technical Paper, 1992.

[19] GN Pontikakis, GS Konstantas, and AM Stamatelos. Three-way catalytic converter modeling as a modern engineering design tool. Journal of engineering for gas turbines and power, 126(4):906–923, 2004.

[20] Evangelos Gonatas and Richard Stobart. Prediction of gas concentrations in a three-way catalyst for on-board diagnostic applications. Technical report, SAE Technical Paper, 2005.

[21] Erich P Brandt, Yanying Wang, and Jessy W Grizzle. Dynamic modeling of a three-way catalyst for si engine exhaust emission control. IEEE Transactions on control systems technology, 8(5):767–776, 2000.

[22] Kenneth R Muske and James C Peyton Jones. Estimating the oxygen storage level of a three-way automotive catalyst. 5:4060–4065, 2004.

[23] Robert W Schallock, Kenneth R Muske, and James C Peyton Jones. Model predictive functional control for an automotive three-way catalyst. SAE International Journal of Fuels and Lubricants, 2(1):242–249, 2009.

[24] Mario Balenovic. Modelling and model-based control of a three-way catalytic converter. University of Eindhoven, 2002.

[25] Lennart Ljung Torkel Glad. Reglerteori - Flervariabla och olinjära metoder. Studentlitteratur, 2016.

[26] Mario Balenović, Jerome Edwards, and Ton Backx. Vehicle application of model-based catalyst control. Control Engineering Practice, 14(3):223–233, 2006.

[27] Svante Gunnarson Peter Lindskog Lennart Ljung Johan Löfberg Thomas McKelvey Anders Stenman Jan-Erik Strömberg Martin Enquist, Torkel Glad. Industriell Reglerteknik Kurskompendium. Reglerteknik, Institutionen för systemteknik, Linköpings universitet, 2014.

1. History of Reducing Air Pollution from Transportation in the United States. (2017, Feb 28). Retrieved from https://www.epa.gov/air-pollutiontransportation/accomplishments-and-success-air-pollution-transportation

2. Rachel. K. (2016, Aug 15). How Public Transit can Help Reduce Carbon Pollution. Retrieved from https://transitscreen.com/blog/how-public-transit-can-and-must-helpreduce-carbon-pollution/

3. Newman. J. (2011, Jan 7). Environmental Benefits of Public Transport. Retrieved from https://www.southuniversity.edu/whoweare/newsroom/blog/environmental-benefitsof-public-transportation-31178

4. Miller. V. (2015, March 15). Record 10.8 Billion Trips Taken on U.S. Public Transportation In 2014. Retrieved from http://www.apta.com/mediacenter/pressreleases/2015/pages/150309_ridership.aspx

5. Port & Marine, Diesel Technology Form. (n.d.). Retrieved from www.dieselforum.org/about-clean-diesel/port-and-marine

6. Sartipi, S., Khodadadi, A. A., & Mortazavi, Y. (2008). Pd-doped LaCoO3 regenerative catalyst for automotive emissions control. Applied Catalysis B: Environmental, 83(3- 4), 214-220.

7. Al Zboon, K. (2009). TREND IN EXHAUST EMISSIONS FROM IN-USE GASOLINE VEHICLES. Environmental Engineering & Management Journal (EEMJ), 8(1).

8. Woodcock, J., Edwards, P., Tonne, C., Armstrong, B. G., Ashiru, O., Banister, D., & Franco, O. H. (2009). Public health benefits of strategies to reduce greenhouse-gas emissions: urban land transport. The Lancet, 374(9705), 1930-1943.

9. Germa. B., Maximilian. H. (n.d.). Evaluation of the Impact of bus Rapid Transit on Air Pollution. Retrieved from http://www.ub.edu/irea/working_papers/2015/201519.pdf

10. Robert. H. (n.d.). Driving Down Diesel Emissions. Retrieved from http://www.accessmagazine.org/wp-content/uploads/sites/7/2015/10/diesel.pdf

11. Morgan, W. K. C., Reger, R. B., & Tucker, D. M. (1997). Health effects of diesel emissions. The Annals of occupational hygiene, 41(6), 643-658.

12. Diesel Emissions Health and Environmental Effects. (n.d.). Retrieved from http://www.mde.maryland.gov/programs/Air/MobileSources/DieselVehicleInformation/HealthandEnvironmentalEffects/Pages/index.aspx

13. Air Province British Columbia. (n.d.) Retrieved from http://www.bcairquality.ca/topics/vehicle-pollutants.html

14. U.S EPA, Mobile Source Emissions-Past, Present, and Future. (n.d.). Retrieved from http://www.epa.gov/otaq/invntory/overview/pollutants/nox.html

15. Air Province British Columbia. (n.d.) Retrieved from http://www.bcairquality.ca/topics/vehicle-emissions-stats.html

16. Air Province British Columbia. (n.d.) Retrieved from http://www.bcairquality.ca/topics/emissions-diesel-buses.html

17. Health Effects of Diesel Exhaust. (2011, May 21). Retrieved from https://oehha.ca.gov/air/health-effects-diesel-exhaust

18. Sydbom, A., Blomberg, A., Parnia, S., Stenfors, N., Sandström, T., & Dahlen, S. E. (2001). Health effects of diesel exhaust emissions. European Respiratory Journal, 17(4), 733-746.

19. Morgan, W. K. C., Reger, R. B., & Tucker, D. M. (1997). Health effects of diesel emissions. The Annals of occupational hygiene, 41(6), 643-658.

20. Camner, P., Pershagen, G., Ahlborg, U., Ljungqvist, S., & Victorin, K. (1988). Health effects of diesel exhaust emissions. Nordic Council of Ministers.

21. Yoshino, S., & Sagai, M. (1999). Enhancement of collagen-induced arthritis in mice by diesel exhaust particles. Journal of Pharmacology and Experimental Therapeutics, 290(2), 524-529.

22. Schwartz, J., Dockery, D. W., & Neas, L. M. (1996). Is daily mortality associated specifically with fine particles? Journal of the Air & Waste Management Association, 46(10), 927-939.

23. Seaton, A., Godden, D., MacNee, W., & Donaldson, K. (1995). Particulate air pollution and acute health effects. The lancet, 345(8943), 176-178.

24. Cicero-Fernández, P., Long, J. R., & Winer, A. M. (1997). Effects of grades and other loads on on-road emissions of hydrocarbons and carbon monoxide. Journal of the Air & Waste Management Association, 47(8), 898-904.

25. United States Environmental Protection agency. (2016, December 20). NAAQs Table. Retrieved from https://www.epa.gov/criteria-air-pollutants/naaqs-table

26. Somuri, D. C. (2011). Study of particulate number concentrations in buses running with bio diesel and ultra-low sulfur diesel.

27. American Lung Association Clean Air Choice: Clean Fuels: CNG & LPG. (n.d.). Retrieved from http://www.cleanairchoice.org/fuels/cng.cfm

28. Durbin, T. D., Collins, J. R., Norbeck, J. M., & Smith, M. R. (2000). Effects of biodiesel, biodiesel blends, and a synthetic diesel on emissions from light heavy-duty diesel vehicles. Environmental science & technology, 34(3), 349-355.

29. Knothe, G., Sharp, C. A., & Ryan, T. W. (2006). Exhaust emissions of biodiesel, petro diesel, neat methyl esters, and alkanes in a new technology engine. Energy & Fuels, 20(1), 403-408.

30. Tat, M. E., Wang, P. S., Van Gerpen, J. H., & Clemente, T. E. (2007). Exhaust emissions from an engine fueled with biodiesel from high-oleic soybeans. Journal of the American Oil Chemists' Society, 84(9), 865-869.

31. Yarlagadda, M. (2016). An analysis of NOx and PM emissions in idle and moving conditions of buses with EGR and Non-EGR engines running on biodiesel (Doctoral dissertation, University of Toledo).

32. Correa, S. M., & Arbilla, G. (2006). Aromatic hydrocarbons emissions in diesel and biodiesel exhaust. Atmospheric Environment, 40(35), 6821-6826.

33. Faiz, A., Weaver, C. S., & Walsh, M. P. (1996). Air pollution from motor vehicles: standards and technologies for controlling emissions. World Bank Publications.

34. Ergeneman, M., Sorusbay, C., & Goktan, A. G. (1999). Exhaust emission and fuel consumption of cng diesel fueled city buses calculated using a sample driving cycle. Energy sources, 21(3), 257-268.

35. Shandilya, K., & Kumar, A. (2014). Carbon speciation of exhaust particulate matter of public transit buses running on alternative fuels. Fuel, 115, 678-684.

36. Chauhan, B. S., Kumar, N., & Cho, H. M. (2012). A study on the performance and emission of a diesel engine fueled with Jatropha biodiesel oil and its blends. Energy, 37(1), 616-622.

37. Szybist, J. P., Boehman, A. L., Taylor, J. D., & McCormick, R. L. (2005). Evaluation of formulation strategies to eliminate the biodiesel NOx effect. Fuel Processing Technology, 86(10), 1109-1126.

38. Can, Ö., Öztürk, E., & Yücesu, H. S. (2017). Combustion and exhaust emissions of canola biodiesel blends in a single cylinder DI diesel engine. Renewable Energy, 109, 73-82.

39. Hoekman, S. K., & Robbins, C. (2012). Review of the effects of biodiesel on NOx emissions. Fuel Processing Technology, 96, 237-249.

40. Vijayan, A., Kumar, A., & Abraham, M. (2008). Experimental analysis of vehicle operation parameters affecting emission behavior of public transport buses with alternative diesel fuels. Transportation Research Record: Journal of the Transportation Research Board, (2058), 68-78.

41. McCormick, R. L., Williams, A., Ireland, J., & Hayes, R. R. (2006). Effects of biodiesel blends on vehicle emissions: fiscal year 2006 annual operating plan milestone 10.4 (No. NREL/MP-540-40554). National Renewable Energy Laboratory (NREL), Golden, CO..

42. Mueller, C. J., Boehman, A. L., & Martin, G. C. (2009). An experimental investigation of the origin of increased NO x emissions when fueling a heavy-duty compressionignition engine with soy biodiesel. SAE International Journal of Fuels and Lubricants, 2(2009-01-1792), 789-816.

43. Eckerle, W. A., Lyford-Pike, E. J., Stanton, D. W., LaPointe, L. A., Whitacre, S. D., & Wall, J. C. (2009). Effects of methyl ester biodiesel blends on NOx emissions. SAE International Journal of Fuels and Lubricants, 1(1), 102-118.

44. Choi, C. Y., & Reitz, R. D. (1999). An experimental study on the effects of oxygenated fuel blends and multiple injection strategies on DI diesel engine emissions. Fuel, 78(11), 1303-1317.

45. Kim, M. Y., Yoon, S. H., & Lee, C. S. (2008). Impact of split injection strategy on the exhaust emissions and soot particulates from a compression ignition engine fueled with neat biodiesel. Energy & Fuels, 22(2), 1260-1265.

46. Kegl, B. (2008). Effects of biodiesel on emissions of a bus diesel engine. Bio resource technology, 99(4), 863-873.

47. Muncrief, R. L., Rooks, C. W., Cruz, M., & Harold, M. P. (2008). Combining biodiesel and exhaust gas recirculation for reduction in NO x and particulate emissions. Energy & Fuels, 22(2), 1285-1296.

48. Pierpont, D. A., Montgomery, D. T., & Reitz, R. D. (1995). Reducing particulate and NOx using multiple injections and EGR in a DI diesel (No. 950217). SAE Technical Paper.

49. Özçelik, A. E., Aydoğan, H., & Acaroğlu, M. (2015). Determining the performance, emission and combustion properties of camelina biodiesel blends. Energy Conversion and Management, 96, 47-57.

50. López, J. M., Jiménez, F., Aparicio, F., & Flores, N. (2009). On-road emissions from urban buses with SCR+ Urea and EGR+ DPF systems using diesel and biodiesel. Transportation Research Part D: Transport and Environment, 14(1), 1-5.

51. Kumar, A., & Nerella, V. K. V. (2009). Experimental analysis of exhaust emissions from transit buses fuelled with biodiesel. Open Environmental Engineering Journal, 2, 81-96.

52. Alptekin, E., Canakci, M., Ozsezen, A. N., Turkcan, A., & Sanli, H. (2015). Using waste animal fat based biodiesels–bioethanol–diesel fuel blends in a DI diesel engine. Fuel, 157, 245-254.

53. Senda, J., Okui, N., Tsukamoto, T., & Fujimoto, H. (2004). On-board measurement of engine performance and emissions in diesel vehicle operated with bio-diesel fuel (No. 2004-01-0083). SAE Technical Paper.

54. Shukla, A., & Alam, M. (2010). Assessment of real world on-road vehicle emissions under dynamic urban traffic conditions in Delhi. International Journal of Urban Sciences, 14(2), 207-220.

55. Kumar, A., Kim, D. S., Omidvarborna, H., Yarlagadda, M., Kuppili, S. K., & Sawtarie, N. (2016). Experimental Modeling of NOx and PM Generation from Combustion of Various Biodiesel Blends for Urban Transport Buses.

56. Yun, B. K., & Kim, M. Y. (2013). Modeling the selective catalytic reduction of NOx by ammonia over a Vanadia-based catalyst from heavy duty diesel exhaust gases. Applied Thermal Engineering, 50(1), 152-158.

57. Zheng, M., & Banerjee, S. (2009). Diesel oxidation catalyst and particulate filter modeling in active–flow configurations. Applied Thermal Engineering, 29(14-15), 3021-3035.

58. Brandt, E. P., Wang, Y., & Grizzle, J. W. (2000). Dynamic modeling of a three-way catalyst for SI engine exhaust emission control. IEEE Transactions on control systems technology, 8(5), 767-776.

59. Kennedy. D. (2011, May 1). The Evil of EGR on Diesel Engines. Retrieved from http://www.trucktrend.com/how-to/engine/1105dp-the-evil-of-egr-on-diesel-engines/

60. Gavin. H. (2011). The Levenberg-Marquardt method for nonlinear least squares curve fitting problems.

61. Wilamowski, B. M., Iplikci, S., Kaynak, O., & Efe, M. O. (2001). An algorithm for fast convergence in training neural networks. In Neural Networks, 2001. Proceedings. IJCNN'01. International Joint Conference on (Vol. 3, pp. 1778-1782). IEEE.

62. Ganesan, P., Rajakarunakaran, S., Thirugnanasambandam, M., & Devaraj, D. (2015). Artificial neural network model to predict the diesel electric generator performance and exhaust emissions. Energy, 83, 115-124.

63. Ghobadian, B., Rahimi, H., Nikbakht, A. M., Najafi, G., & Yusaf, T. F. (2009). Diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an artificial neural network. Renewable Energy, 34(4), 976-982.

64. Najafi, G., Ghobadian, B., Tavakoli, T., Buttsworth, D. R., Yusaf, T. F., & Faizollahnejad, M. (2009). Performance and exhaust emissions of a gasoline engine with ethanol blended gasoline fuels using artificial neural network. Applied Energy, 86(5), 630-639.

65. Kumar, A., Kim, D. S., Omidvarborna, H., Yarlagadda, M., Kuppili, S. K., & Sawtarie, N. (2016). Experimental Modeling of NOx and PM Generation from Combustion of Various Biodiesel Blends for Urban Transport Buses.

66. Omidvarborna, H., Kumar, A., & Kim, D. S. (2014). Characterization of particulate matter emitted from transit buses fueled with B20 in idle modes. Journal of Environmental Chemical Engineering, 2(4), 2335-2342.

67. Shandilya, K., & Kumar, A. (2013). Particulate emissions from tailpipe during idle of public transit buses fueled with alternative fuels. Environmental Progress & Sustainable Energy, 32(4), 1134-1142.

68. Lowenthal, D. H., Zielinska, B., Chow, J. C., Watson, J. G., Gautam, M., Ferguson, D. H., & Stevens, K. D. (1994). Characterization of heavy-duty diesel vehicle emissions. Atmospheric Environment, 28(4), 731-743.

69. Bharathi, K. V. L., Dwivedi, D., Agarwal, A. K., & Sharma, M. Diesel exhaust particulates characterization for heavy metals.

70. Wang, W. G., Lyons, D. W., Clark, N. N., Gautam, M., & Norton, P. M. (2000). Emissions from nine heavy trucks fueled by diesel and biodiesel blend without engine modification. Environmental science & technology, 34(6), 933-939.

71. Agarwal, D., Sinha, S., & Agarwal, A. K. (2006). Experimental investigation of control of NOx emissions in biodiesel-fueled compression ignition engine. Renewable energy, 31(14), 2356-2369.

72. Geurts, P., & Louppe, G. (2011). Learning to rank with extremely randomized trees. In JMLR: Workshop and Conference Proceedings (Vol. 14, pp. 49-61).

73. Costa, M., Rodrigues, T., Horta, E., Braga, A., Pataro, C., Natowicz, R., ... & Cela, A. (2009). New Multi-Objective Algorithms for Neural Network Training Applied to Genomic Classification Data. In Foundations of Computational, Intelligence Volume 1 (pp. 63-82). Springer, Berlin, Heidelberg