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ORIGINAL PAPER

A Review of the State-of-the-Art Emission Control Strategies in Modern Diesel Engines

Vaibhav Ahire[1] · Mahesh Shewale[1] · Ali Razban[1]

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Abstract

Accurate prediction and control of diesel engine-out emissions are vital areas of interest for automotive manufacturers and researchers. This article presents an investigative review of performance and emission control improvements in diesel engines over the past few decades. A brief background of environmental organizations like the Environmental Protection Agency has been included because they initiated stringent emission norms. These requirements caused diesel engine development to be a more tedious task and also triggered various technologies employed by engine manufacturers to meet the new norms. This review focuses on various diesel engine modeling methods that have evolved during the last few decades and have contributed to the technological advancement in modern diesel engines. Three types of modeling methods and their applications are discussed in detail along with a few controlling methods using different control theories. A detailed emphasis on recent engine control strategies reviews controlling gridlocks and viable solutions in diesel engines. Significant challenges such as model fitness, accuracy, robustness, and precise predictions that provide extensive scope for researchers working in diesel engine out emission control are addressed. Various advancements in optimized engine model development for further performance enhancement are also reported.

Abbreviations

0-D	0 Dimensional
AHRR	Apparent Heat Release Rate
ANN	Artificial Neural Network
BSFC	Brake Specific Fuel Consumption
BTS	Bureau of Transportation Statistics
CAA	Clean Air Act
CAD	Crank Angle Degrees
CI	Compression-Ignition
CMAC	Cerebellar Model Articulation Controller
CN	Cyanide
CO	Carbon Monoxide
DOF	Degree of Freedom
DPF	Diesel Particulate Filter
ECM	Electronic Control Module
ECU	Engine Control Unit
EGR	Exhaust Gas Recirculation
EO	Engine Out
EOI	End of Injection
EPA	Environmental Protection Agency
ETA	Electric Turbo Assist
FB	Feedback
FEL	Feedback Error Learning
FF	Feedforward
FHWA	Federal Highway Administration
FMI	Functional Mockup Interface
GT Suite	Gamma Technologies Suite
HCCI	Homogenous Charged Compression Ignition
HCN	Hydrogen Cyanide
HDE	Heavy-Duty Engines
HDV	Heavy-Duty Vehicle
HiL	Hardware in Loop
HRR	Heat Release Rate
IC	Internal Combustion
LL	Liquid Length
LOL	Lift-Off Length
LQG	Linear Quadrature Gaussian
MiL	Model in Loop
MPC	Model Predictive Control
N_2	Nitrogen molecule

✉ Ali Razban
arazban@iupui.edu

Vaibhav Ahire
vahire@iu.edu

Mahesh Shewale
mshewale@iupui.edu

[1] Department of Mechanical and Energy Engineering, Indiana University Purdue University Indianapolis, Indianapolis, IN 46202, USA

N_2O	Nitrous Oxide
NH_2	Azanide
NH_3	Ammonia
NOE	Nonlinear Output Error
NO_x	Nitrogen Oxides
OBD	On-Board Diagnosis
OICA	Organisation Internationale des Constructeurs d'Automobiles
OLL	Optimization layer-by-layer
PCCI	Premixed Charge Compression Ignition
PI	Proportional Integral
PID	Proportional Integral and Derivative Controller
RNN	Recurrent Neural Network
SCR	Selective Catalytic Reduction
SiL	Software in Loop
SOC	Start of Combustion
SOI	Start of Injection
TDE	Turbocharged Diesel Engine
UHC	Unburnt Hydrocarbon
VGT	Variable Geometry Turbine
VMT	Vehicle Miles Traveled
VNT	Variable Nozzle Turbine
VOCs	Volatile Organic Compounds
VVA	Variable Valve Actuation
VVT	Variable Valve Turbine

1 Introduction

The number of United States-registered on-road vehicles has increased from 8000 to 268 million during the last few decades (Bureau of Transportation Statistics [BTS] 2016; Federal Highway Administration [FHWA] 1997) [1]. As a result, vehicle miles traveled (VMT) have increased by almost 690% while there has been only a 25% increase in road miles constructed in the United States (U.S.) from 1950 to 2016 [2]. Although the increase in road miles has been minimal, during the last few decades, technological development in fuel economy has contributed to the significant increase in the number of global on-road operational vehicles to nearly 1.3 billion even though in 2015, the U.S. reported 821 motor vehicles per 1000 people (International Organization of Motor Vehicle Manufacturers- [OICA] 2015) [3]. The increase in the number of on-road vehicles is proportional to the number of hazardous by-products emitted by internal combustion (IC) engine vehicles: This negatively impacted air quality, gave birth to several respiratory diseases, and even cause premature deaths. By 1970, U.S. national emissions were largely produced by on-road vehicles consisting of 35% nitrogen oxides (NO_x), 68% carbon monoxide (CO), and 42% volatile organic compounds (VOCs) [4].

As a response, the Environmental Protection Agency (EPA) mandated the first national vehicle emissions standards in the 1970 Clean Air Act (CAA). The EPA has continued to issue stringent laws regarding tail-pipe emissions from both gasoline and diesel engine vehicles from 1990 to 2017 [5]. Figure 1 shows the evolution of the U.S. vehicle emission compliance and control program [6].

This review is limited to diesel engine technologies since these vehicles contribute to more vehicle miles traveled (VMT) than gasoline vehicles as shown in Fig. 2. The diesel engine VMT number illustrates the need for their development in terms of fuel economy and emissions. As a result, automotive manufacturers are endeavoring to meet the EPA emission regulations by introducing new emission control strategies that enhance the fuel economy at the same time. Some of the technologies—electronically-controlled fuel injection, exhaust gas recirculation (EGR), catalytic converters, particle filters, etc. have been introduced by vehicle manufacturers [7]. Later, on-board diagnosis (OBD) devices/systems were mandated to ensure the emission control devices and to monitor faults if any.

Diesel engine vehicles are mostly long-haul, medium-duty to heavy-duty vehicles/trucks/buses (HDV) with heavy-duty engines (HDE), and their total fuel consumption is greater than gasoline vehicle consumption, ultimately resulting in more emissions than gasoline vehicles [8]. This article discusses various control strategies to reduce EO emissions and the different methodologies involved. The first section enumerates the need for numerical investigation of diesel engine combustion followed by the state of the art of diesel engine combustion modeling. Furthermore, controller development methods are discussed to facilitate an understanding of each controlling approach. The last section focuses on the recent strategies applied in both modeling and controller design and optimization. In the end, a detailed summary is given to highlight the research gaps and the future scope for researchers.

While a few reviews which have recently been published focus on alternative fuel blend strategies to reduce emissions with the optimum performance [9–11] and a few cover cylinder states estimation methods, empirical methods based on experimental data, and hybrid diesel engine control techniques [12, 13], all of these articles lack in reviewing the controlling strategies that are needed to address bridging the microscopic gap between state of the art and future emission goals. This work focuses on a discussion that covers work related to accurate combustion modeling and effective control strategies. Specifically, it covers recent strategies that are needed for precise combustion control to achieve the EPA Tier 3 emission standards without changing existing engine architectures.

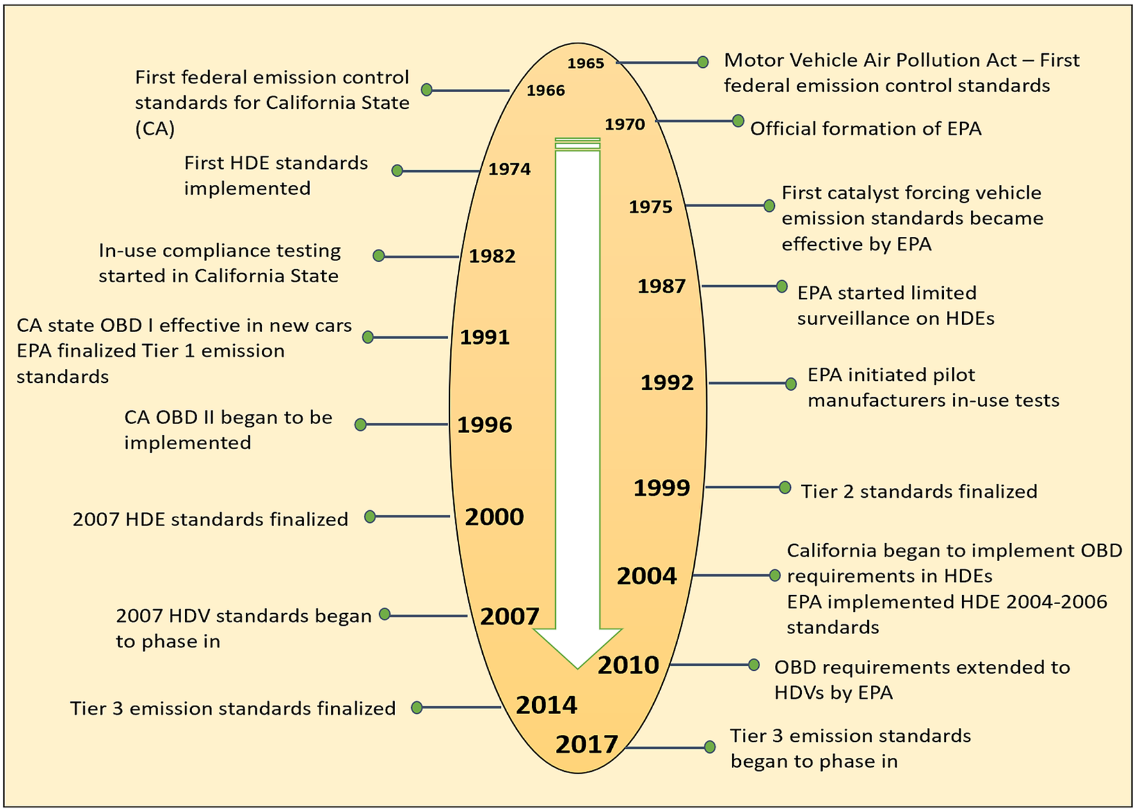

Fig. 1 History of the U.S. emissions compliance and control programs

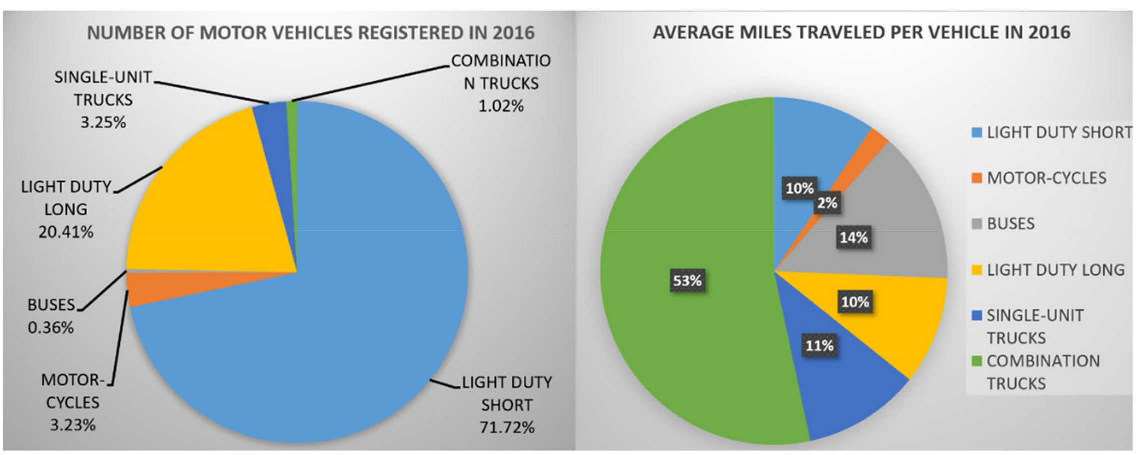

Fig. 2 Annual vehicle registered and distance traveled in miles and related data—2016 FHWA

2 Numerical Investigation of Diesel Engine Combustion and EO Emissions

This section provides a detailed discussion of Combustion Modeling. Detailed combustion modeling helps in understanding the different degrees of freedom involved in modern engines due to advanced technologies. Different methods are based on approaches derived for various applications as explained in further sections.

2.1 Need for Combustion Modeling

Diesel combustion is a heterogeneous chemical process during which the liquid fuel consisting of hundreds of hydrocarbon species interacts with gaseous in-cylinder charge (air) leading to heat release and emission formation. These thermal reactions are influenced by several parameters such as engine geometry, state of the charge mixing with fuel, and residuals from combustion. Based on this combustion principle, engine manufacturers have developed such technologies such as Variable Valve Technology (VVT), Electronics Fuel Injection Systems, Turbochargers, Superchargers, EGR, and After Treatment Systems. These techniques aim for optimal fuel consumption and emission reduction in both the tailpipe and the cylinder causing engine control to be a complex task. As a result, developers have a new task: the need to understand this complex phenomenon. Combustion models are valuable tools to aid in the understanding of the combustion process and have led to new technological insights that have yielded better fuel efficiency and reduced emissions. Figure 3 shows added technologies with multiple degrees of freedom to meet both driver and legislative demands over the past few decades [14].

The complexity of engine control strategies has dramatically increased due to multiple degrees of freedom and the inevitable time and cost constraints for controller design and development cycles. Engine Models accelerate the engine development cycles since components or systems can be modeled in early phases and can then be optimized by testing these virtual engines without costly test cells [14]. 'Model-Based Control' saves calibration and testing time by using real-time combustion models in transient engine control [15, 16]. Isermann et al. described a systematic procedure for model-based design of the multi-variable control function of IC engines, which considers both steady-state and transient behaviors yielding optimal control of fuel consumption and emissions. The models are verified with the model uncertainty optimization using the Global Optimization method and smoothing the local optimal setpoints [17].

Isermann and his colleagues divided the engine control system into function development and function calibration. Based on the functional requirements, systems are modeled using different approaches as discussed in later sections of this review. These models are tested in the loop (model in loop—MiL) with the actual system testing the preliminary fitness. Developed functions provide a baseline for the controller development and simulation, which can then be calibrated. Successfully calibrated models provide the source codes for engine control unit (ECU) that are implemented in real-time simulations for a final check before deploying to the system. The workflow of model-based design is formulated in Fig. 4 and indicates that the system modeling is the first milestone in engine development and testing [17]. An important component of function development requires the fundamental understanding of diesel engine combustion that

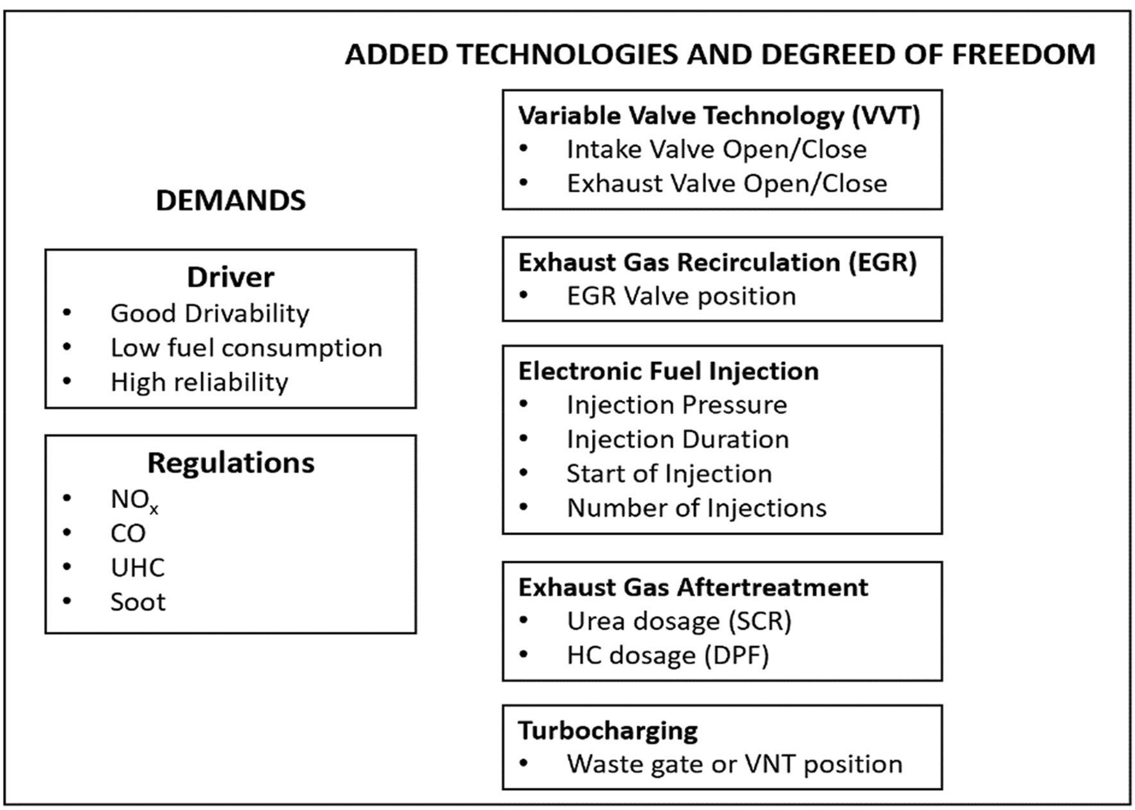

Fig. 3 Overview of demands placed on the compression Ignition (CI) engine and added new technologies

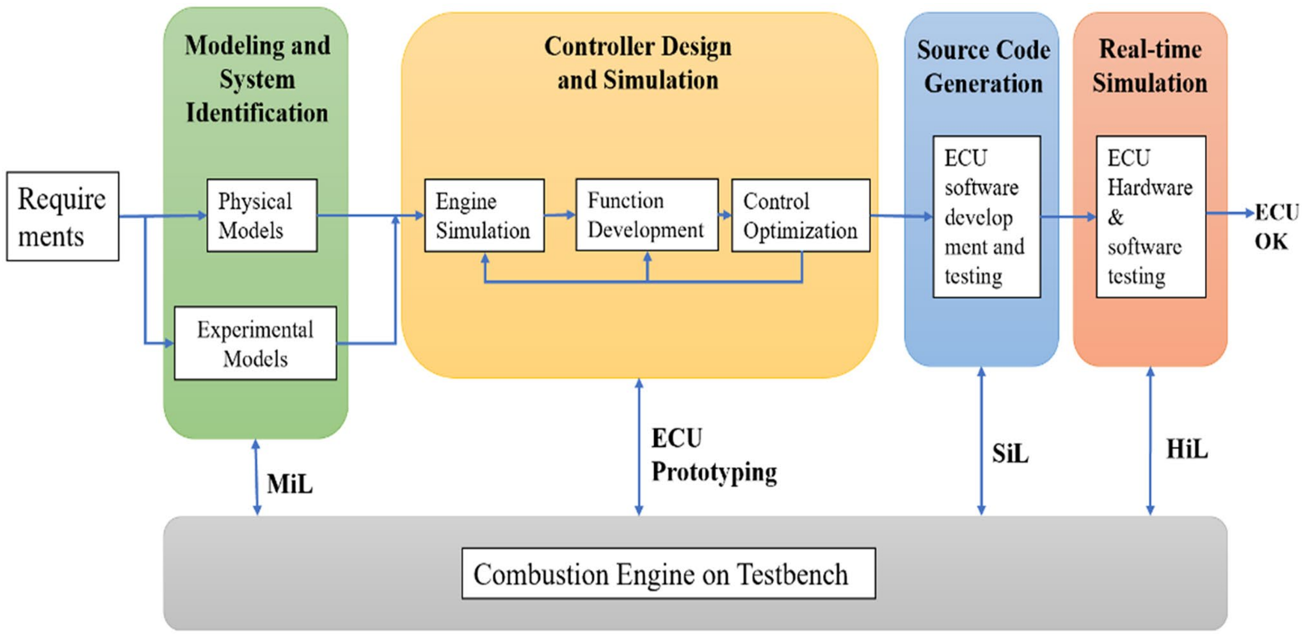

Fig. 4 The workflow of model-based design

involves various systems depending on the type and application. To understand the diesel engine combustion, one needs to understand different methods of modeling the combustion phenomena, engine operations considering both inputs and outputs, and complexity based on the advancement through past decades. The next section gives an overview of engine modeling techniques for better understanding.

2.2 Combustion Models

One of the major challenges in Diesel Engine Combustion is estimation and control of combustion characteristics which are affected by multiple factors: fuel–air properties, crank angle based events like intake valve closing (IVC), intake valve opening (IVO), start of injection (SOI), end of injection (EOI), start of combustion (SOC), etc., and additional engine-dependent parameters such as geometry and specification [18, 19]. The complexity and computational efforts are based on the number of these parameters involved in the modeling. Hence detailed and accurate diesel engine modeling is at utmost priority. These models are categorized into three types:

1. Empirical models.
2. Phenomenological models.
3. Physics-based models.

2.2.1 Empirical Combustion Models

This method considers combustion as a "Black Box" and is based on the input and output data taken from experiments for defined operating conditions. Neural networks, correlations, and look-up tables are the hallmarks of the Empirical Model. Watson et al. 2010, performed several experiments on three different engines to establish the relationship between engine operating parameters and the apparent heat release rate (AHRR) [20]. The study included finding a correlation between engine operating parameters and respective heat release rates that are effective only for coarser crank angle (CAD) intervals. These models were adaptive for parametric changes in performance parameters like compression ratio, valve timing, valve areas, injection timing, aftercooling, ambient conditions, etc. but could not be used to predict the effect of the combustion chamber design changes. Weibe, Wolfer, and Woschni et al. all derived the correlations between ignition delay and pressure, temperature, SOI and EOI which help to calculate the heat release rated based on experimental measurements [21–23]. This approach includes the calculation of mass burned fractions, which leads to the prediction of emissions. They derived the shape factors and empirical constants for their correlations based on specific operating conditions. For the last couple of decades, look-up tables have been widely used in the industry for engine calibration and control and are proven to be effective calibration models, but they are not accurate in terms of handling uncertainties in real-operating conditions.

The development time for the look-up tables is too long to develop rapid solutions. Some applications of look-up tables in controller development along with new strategies to overcome these disadvantages are discussed in Sect. 4.

Artificial Neural Networks (ANN) are the latest tools being used to predict the cylinder states and emissions based on correlations derived from specific operating conditions. The ANN learning rule is classified as either supervised or unsupervised. Supervised learning rules adapt the weights of the network to reduce the error between the network output and measured output. Krijnsen et al. 1999 evaluated the application of a neural network to predict NOx from a transient diesel engine cycle to control NOx in catalytic reduction devices [24]. They compared their work with the traditional linear fit and engine map models and achieved accuracy up to 93.4% against linear fit (~83.8%) and engine map (~82.5%) with a short calculation time of 0.2 ms. Daniel Lee et al. developed a model that aids in simulating the combustion procedure of diesel engines using probability density function [25]. This model could predict some of the major features of diesel engine combustion, but simulated pressure traces for a few conditions produced hyperbolic results. Parlak et al. investigated how accurately the artificial neural network model can predict the exhaust temperature as well as the specific fuel consumption of a diesel engine when the injection duration is changed [26]. However, the ANN method is developed for specific engines; therefore, relationships derived from this method cannot be used for generic operating conditions and are prone to errors if extrapolated outside of the given experimental conditions. There are, however, some applications in feedforward (FF) and supervised controller for engine control that are discussed later in Sect. 4.

2.2.2 Phenomenological Combustion Models

In this model type, combustion variables are predicted using simple, physical models that replicate the physical and chemical phenomena occurring during the combustion process. Phenomenological models can be categorized into zero-dimensional and quasi-dimensional models. In the case of fuel spray phenomena, the model is subdivided into "packages" or "zones" which have no actual spatial coordinates, hence the name "quasi-dimensional" [27–31]. Heat release and emission formation are predicted for each package or zone. The number of packages or zones depends on the chosen model approach and can range from as few as two to as many as several hundred. The computational effort and time increase with the applied number of zones. The zero-dimensional models are generally only able to predict the heat release rate [32, 33]. For emission formation prediction, at least two zones are required. Several attempts are made to capture the actual phenomenology for the flame formation and different emission formation. The fuel flame

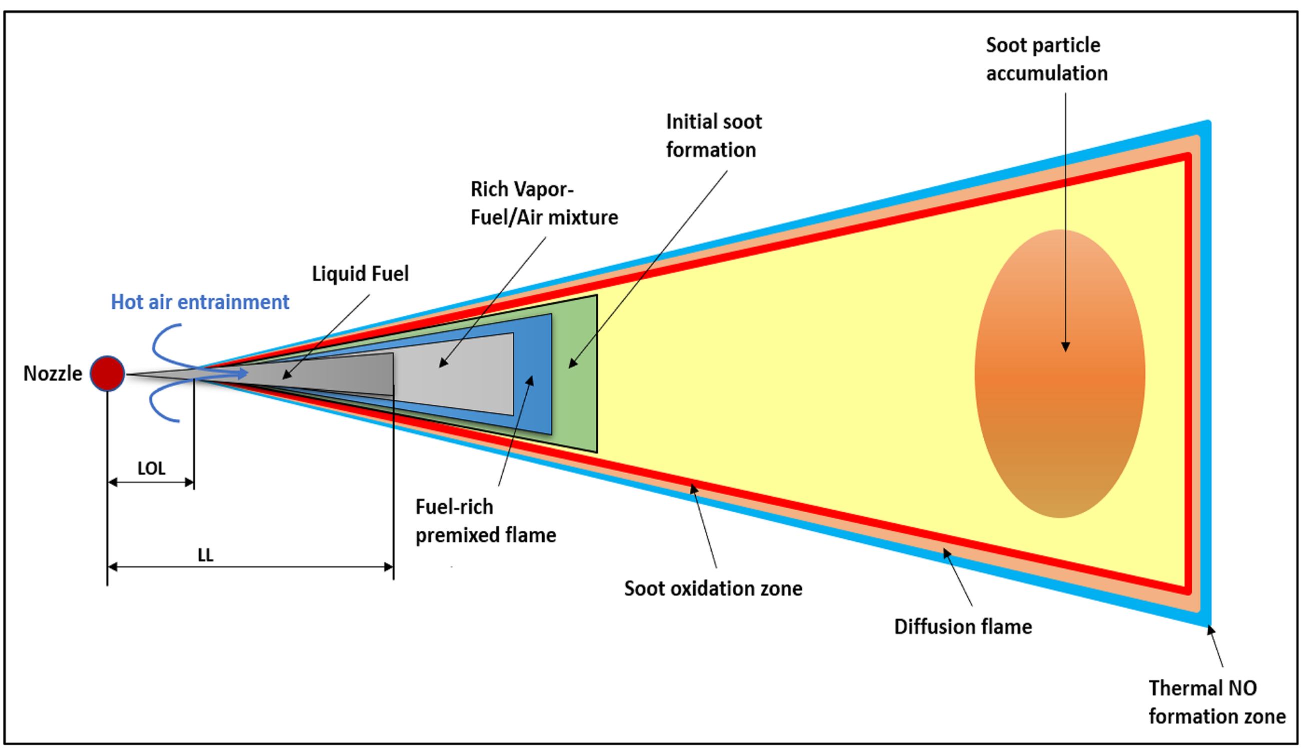

Fig. 5 Schematic representation of quasi-steady burning fuel spray

processing of high-pressure diesel jets is represented by normalized laser-induced imaging, which helps to analyze the different zones in a combustion process [34]. Figure 5 shows the representation of a burning fuel spray showing different regions. It represents the different regions like lift of length (LOL), liquid length (LL) followed by various regions that indicate nitric oxide (NO) and Soot formation based on the fuel spray phenomenology [35]. Before such advancement in imaging technology, only a few people whose work is categorized into three types studied the chemical phenomenon for NO and Soot Formation:

(1) Thermal NO proposed by Zeldovich Y [36] was later extended by Lavoie [37] and is now referred to as the extended "Zeldovich mechanism".
(2) NO formation via the prompt-NO mechanism also referred to as the Fenimore mechanism after Fenimore C [38], occurs when fuel-rich flames in the presence of hydrocarbon radicals react with nitrogen (N_2) to form hydrocyanic acid (HCN).
(3) Wolfrum, postulated the nitrous oxide (N_2O) intermediate pathway [39]. This describes NO formation via nitrous oxide N_2O as an intermediate species formed when nitrogen is attacked by atomic oxygen and a third-body molecule.

The NO formation from fuel-bound nitrogen occurs when fuels containing significant amounts of nitrogen combust, resulting in significant NO formation when thermal decomposition causes the large fuel molecule to break into smaller fragments like ammonia (NH_3), azanide (NH_2), imidogen (NH), HCN, and cyanide (CN) [40]. For coal combustion, experimental models have shown that fuel-Nitrogen is converted to the intermediate species HCN and NH_3, which leads to further NO or N_2 formation by branching reactions using free radicals; this conversion is dependent on local combustion conditions [40]. Flynn et al. utilized laser diagnosis techniques both to observe soot formation and to validate the empirical work based on chemical kinetics [35]. This study encouraged more people to research the piecewise modeling of a combustion flame. Tree et al. [41], studied the soot formation process and discussed the effects of fundamental properties like temperature, pressure, stoichiometry, and fuel consumption. They revealed the complexity of the phenomenological models regarding the number of formation zones; this is a vital criterion for the accuracy of prediction algorithms. These models generally can predict heat release rates [33, 41].

In contrast to the (semi-)empirical models, the phenomenological models allow (to a certain extent) extrapolation outside of the operating range for which they are originally developed. They have clear predictive capabilities regarding both heat release rate and emission formation. Understanding the combustion phenomena is key when using this type of modeling approach. For emissions, more detailed data—a combination of both phenomenology and empirical—is required which limits the use of these zero-dimensional (0-D) models. Moreover, the prediction of a certain phenomenon depends on various driving inputs that are required to be modeled if the physical measurement is not possible because of the sensing limitations. For instance, the NO_x model is based on the in-cylinder pressure and temperature traces. Understanding the chemical kinetics inside the cylinder plays a vital role in predicting the heat release rates that drive combustion states in a cylinder. With the latest technologies involved in the diesel engine control, it is essential to model these complex systems for better prediction results. The next section focuses on such Physics-Based models for the different systems in modern diesel engines.

2.2.3 Physics-Based Combustion Models

Physics-based models illustrate the physical and chemical processes that occur during combustion with the highest level of detail. The physical model is on the microscopic level of detailing and combustion events are discrete. The combustion chamber is divided into numerous local systems, which have their dimensions and degrees of freedom. For every local system, full conservation equations for mass, energy, and momentum are solved. As a result, these models have the greatest predictive qualities: emission formation and heat release rate prediction are possible, and models are generic. In 1998, Guzzella, L. et al. [42], devised a detailed model for a diesel engine considering the fuel injection system, EGR, and turbochargers. They were able to model the fuel–air path and EGR path with a turbocharger effect to evaluate the performance and fuel efficiencies taking emissions in the loop. Figure 6 shows the various systems (cells) taken in the gas exchange model considering the EGR fraction effect [42]. This diagram depicts the detailed factors considered as gas mixes in a running engine equipped with EGR.

The system is divided into the intake manifold (fresh gas mass), exhaust manifold (exhaust mass), fuel injection system (injected and burnt fuel mass), combustion chamber (gas exchange inside the combustion chamber) and EGR system which are integrated to account for the re-circulated masses in the cylinder. These local systems can be cycle-to-cycle based or CAD-based depending on the phenomena and its occurrence range. For instance, gas exchange processes are based on the combustion cycle, and the heat release rate is obtained based on CAD for the respective combustion cycle.

The creation of parametric and non-parametric models to control fuel-injection timings for both steady-state and transient operation by Guzella and his colleagues set an engine control research baseline for future researchers [42].

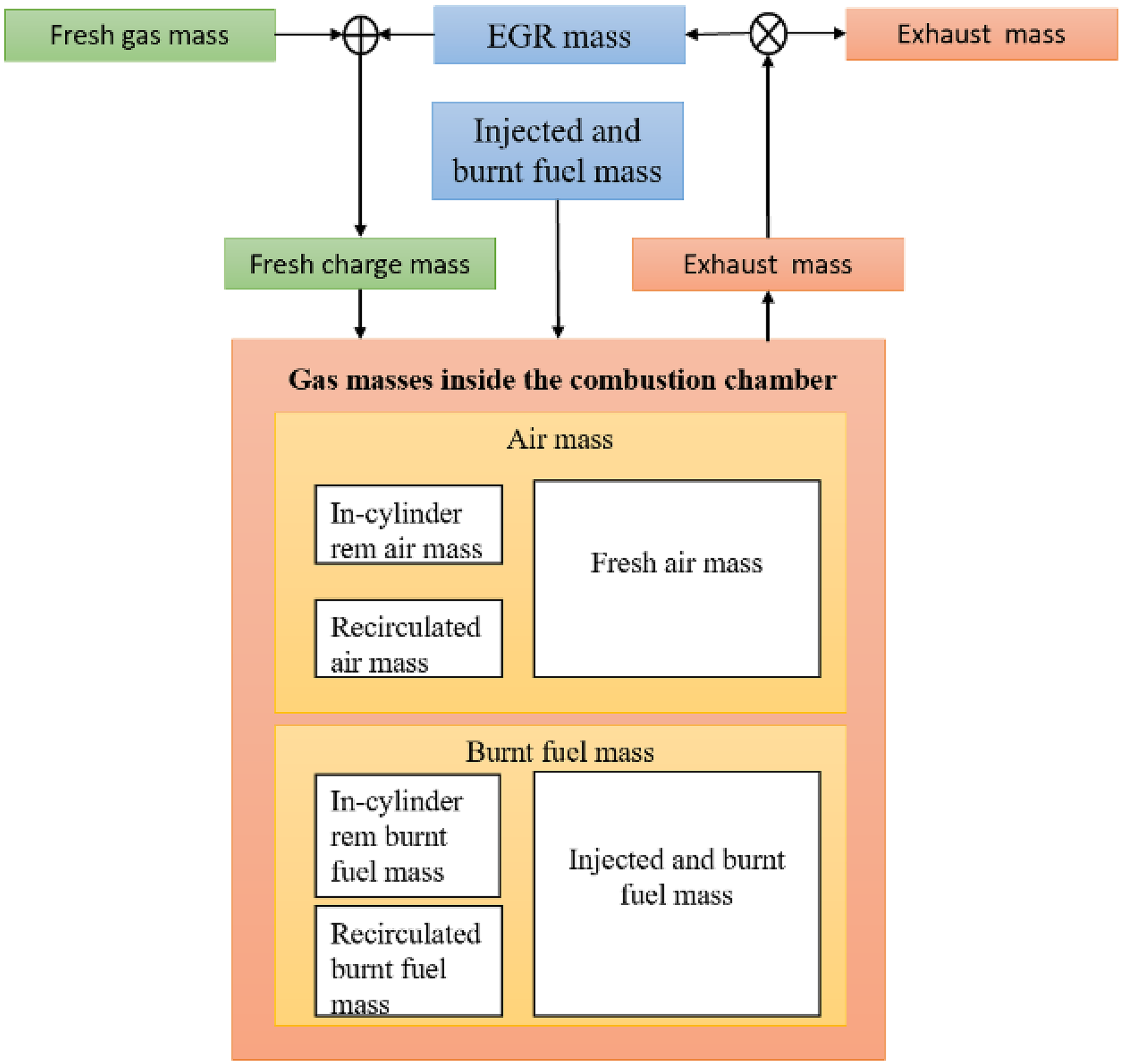

Fig. 6 Basic engine model including EGR

As innovative as Guzella's work was, it did have limitations due to technological deficits. Several factors like detailed NO_x modeling based on recently extended techniques, robust controllers, and multipoint electronic fuel injection technology were not included by Guzzella's work. Figure 7 gives an example of speed and start of fuel injection control as a part of an engine control model. This illustration describes the factors affecting the different control parts like speed, torque, emissions, and drivability. The model presented is a Mean Value Engine Model that includes averaged states estimated during each combustion cycle. These models are transient in macroscopic effects and more simplified to reduce complexity. Such models are convenient to apply in the online control of diesel engines because of their simplicity.

Gas exchange models are an effective tool to control the effective air–fuel ratio (lambda) by modeling both intake and exhaust manifolds including both EGR and Turbo effects. A realistic online Engine Model as a function of CAD (Crank Angle Degrees) was developed by a few researchers and includes both combustion and gas (air–fuel mixture) exchange models. This model uses 0.1 CAD resolution with 90% less computational time, which was accurate up to 10.4% mean relative error in NO formation [43]. Oxygen sensors (Lambda Sensor) are used to measure the oxygen

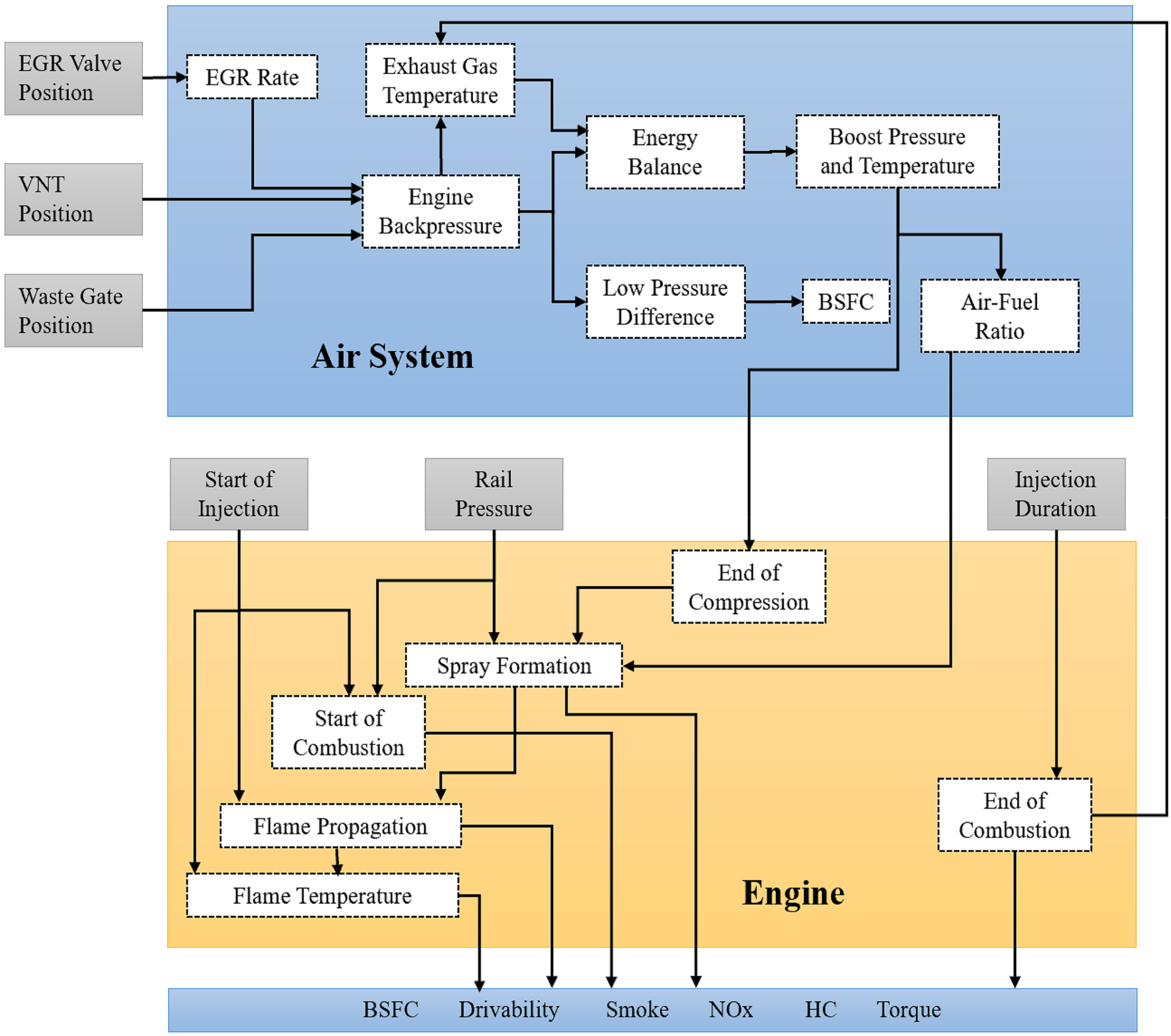

Fig. 7 Control scheme for speed and start of fuel injection control

fraction in both intake and exhaust manifolds while controllers are developed for the optimal fuel injection to maintain the pressure, temperature, and emissions [44]. This modeling approach gives flexibility in modifying the local models to troubleshoot when it is applied online in the electronic controller that directs the engine. This allows researchers to explore local systems in more detail. Guardiola et al. followed a similar approach and developed a cycle by cycle NO_x prediction model. They focused on the NO_x formation that includes various events that depict the formation of thermochemistry and phenomena. This detailed approach focused on the only local models that could make their algorithm 25% more precise than the previous one [45].

Compatibility with different modeling approaches depicts the versatility of the physics-based models. As mentioned above, physics-based mean value engine models are at a significant level of integration compatibility with other models such as empirical, phenomenological, and real-time data acquisition systems. With this advantage, Atkinson et al., applied the dynamic model-based hybrid equations along with neural networks to calibrate the engine for performance and emissions examination. They used virtual sensing methods to map the engine's simulation-based calibration optimization, which can be directly used in the ECU [46]. Because of the complexity of the entire engine model including all new technologies, some authors preferred to work on the actual system and then optimize it for real-time engine control. Data acquisition and post-processing tools like Matlab & Simulink, gamma technologies' GT Suite, Labview, dSPACE, etc., give the freedom to calibrate and optimize the models developed in a more detailed approach [47]. When employing the transient calibration process, the transient models should be trained with the training dataset to achieve accurate model predictions to overcome the effect of the transient operation of engine components [48].

Each model type has drawbacks, be it in accuracy, runtime (speed), operating range, or unprecedented operation disturbances. Therefore, while integrating these models in a real-time complete engine model, numerical optimization of such hybrid models is required to compensate for the drawbacks. Guzzella et al. [49], in their recent work, successfully attempted to simplify the complex engine models into a simple structure. They extracted the most relevant phenomenological elements and extended them into simple empirical elements. Only significant elements were developed into a set point formulator based on the application and reduced the model dimensions significantly. They could reduce the model to a single map (empirical model) and ten scalar parameters only. A significant increase in model speeds – up to 500 times faster than the real-time throughout the engine operating range – had relative errors below 10%. However, this approach had assumptions that are not applicable in modern diesel engines. Factors like multipoint and multiple fuel injection or any fundamental changes due to combustion characteristics were not predicted.

In 2019, Durjarasan et al. [50], developed a control-oriented physics-based model for NO_x emission prediction for a diesel engine equipped with EGR. This work focuses on predicting cycle averaged NO_x with more emphasis on reaction zone modeling and NO_x formation reaction rates. The model predicts in-cylinder pressure based on the heat-release rates and mass burnt fractions. This work covers the entire engine modeling including sub-models (physics-based equations) for each system as well as the impact of major engine control variables like injection and combustion events. This model covers a detailed phenomenon of NO_x formation by including the models for gas exchange, heat release rate, chemical equilibrium solver for adiabatic temperature, temperature compensator for losses, and a detailed NO_x model. These integrated accurate and detailed sub-models achieved 93% prediction accuracy prediction using generic model-based engine control techniques.

Table 1 Empirical combustion modeling summary

Ref. No	Author	Focus	Modeling technique
[20]	Watson et al.	Correlation between engine operating points and AHRR	Experimental Correlations
[21]	Wiebe	Correlation for ignition delay	Experimental Correlations
[22]	Wolfer		
[23]	Woschni et al.		
[24]	Krijnsen et al.	ANN to predict NOx	Linear fit method
[25]	Lee et al.	Combustion Simulation	Probability density function
[26]	Parlek et al.	ANN for exhaust temperature and Brake Specific Fuel Consumption	Experimental Correlations

Table 2 Phenomenological combustion modeling summary

Ref. No	Author	Focus	Modeling technique
[27]	Hiroyasu et al.	Fuel Spray Phenomena packages	Zero Dimensional relations
[28]	Stiesch et al.		
[29]	Stebler et al.	Fuel Spray Phenomena zones	
[30]	Merker et al.		
[31]	Andersson et al.		
[32]	Barba et al.	Heat Release Rates	Zero Dimensional relations
[33]	Chmela et al.		
[34]	Bruneaux et al.	Flame formation and emission formation zones	Laser-induced thermal imaging
[35]	Flynn et al.	Burning fuel spray study and soot formation	Laser-induced thermal imaging
[36]	Zelovich	Zedlovich Mechanism for thermal NOx	Chemical Kinetics
[37]	Lavoie et al.	Extended Zeldovich Mechanism	Chemical Kinetics focused on reaction rates
[38]	Fenimore et al.	NO formation via prompt NO mechanism	Chemical Kinetics
[39]	Wolfrum	NO formation via intermediate pathways	Chemical Kinetics
[40]	Glarborg et al.	NO formation through thermal decomposition of large fuel molecules	Chemical Kinetics
[41]	Tree et al.	Soot formation process with respect to combustion properties	Quasi models for combustion zones

Table 3 Physics-based combustion modeling summary

Ref. No	Author	Focus	Modeling technique
[42]	Guzzella et al.	Detailed model with EGR and Turbo	Mean Value Engine Models from sub-models
[43]	Ericson et al.	Combustion and Gas exchange process	CAD-based engine operation
[44]	Yildiz et al.	Gas Exchange model to control optimal fuel	Cycle by Cycle engine operation
[45]	Guardiola et al.	NOx prediction	Cycle by Cycle engine operation with detailed CAD sub-models
[46]	Atkinson et al.	Virtual sensing method to calibrate engine performance and emission control	Mean Value Engine Models from sub-models along with empirical networks
[49]	Asprion et al.	Simplified physics-based model to increase the computational speed	Extension of phenomenological, physics-based model to empirical mapping to reduce the computational time
[50]	Durjarasan et al.	Virtual NOx sensor development	Mean Value Engine Model with detailed combustion and emission formation kinetics

In conclusion, physics-based models have an advantage in an accurate prediction of in-cylinder states that are required for EO emissions and performance estimation and control. Tables 1, 2, and 3 represent a summary of the Empirical Combustion, Phenomenological Combustion, and Physics-Based Combustion modeling techniques, respectively. Although model speed is of utmost concern, developing such local models and integrating them into the mean value engine models provides both high accuracy and faster prediction when embedded with real-time engine controllers. A few control strategies are discussed in the next sections.

3 Controller Architectures and Implementation

Along with the physical models, prediction models based on control theories play an important role in predicting EO emissions. Different data analysis and filter techniques help train these models to achieve optimal model fitness when applied in real-time applications. Guzzella et al. [42], developed a self-tuning proportional-integral-derivative (PID) controller for speed and fuel injection control based on engine-tested mapping data which was then filtered with the first-order filter. They used the Linear Quadratic Gaussian (LQG) controller type to compare the results and included the self-gain scheduling techniques for auto-tuning. However, they needed to introduce a Smith predictor to reduce delays in the controller as a part of simple lead-lag control; this resulted in required performances with minimized errors. In 2000, an improved fuzzy logical algorithm was proposed which is suitable for self-tuning parameters online in the PID controller. The fuzzy inference mechanism was carried out by the fuzzy control chip F100, and the load and flux of air were treated as controlling parameters in the diesel engine fuzzy controller. The simulation results showed that the on-line fuzzy logic regulation of PID parameters used in the PID controller expanded the range of dynamic response of the controller in the case of loads [51]. A comparative study of two types of controllers for manipulating EGR and variable geometry turbocharger (VGT) actuators to minimize the fuel consumption and pumping losses was done by Wahlström et al., 2009 [52]. A first control structure consisting of PID controllers and min/max-selectors was developed based on a systematic analysis of the model. This controller achieved all control objectives but increased pumping losses by 26% because of the sign reversal in direct current (DC) gains. Another controller with a non-linear compensator was used in the inner loop for handling the non-linear effects along with the PID controller and selectors in an outer loop like the first one. This second approach reduced the EGR errors but increased the pumping losses as compared to the first control structure. Based on these results, they recommended the first structure if there is no non-linear behavior in system feedback (FB).

A new strategy based on a fuzzy multi-variable controller was proposed by Arnold et al. in 2006 to regulate both the fresh airflow and the intake manifold pressure. They used additional weight functions to compensate for oscillation in system input. Additionally, a significant improvement in desired setpoint tracking and the in-time response was obtained as compared to results gained from an embedded PID. This strategy was designed to implement the ECU for real-time applications [53]. The air system controller required neither an internal model nor a certain feed-forward map. This was more robust than previous findings and was an improved technique in terms of time response as compared to readymade embedded controllers. For model simplicity, a dynamic feedback linearization technique was used for tracking the problem for a turbocharged diesel engine (TDE) equipped with an EGR valve and VGT. For enhanced simplicity, the third-order mean-value model controller was used instead of the eighth order-mean value controller [54].

In 2010, another approach was taken to reduce the models; a flatness-based feed-forward controller was designed for a diesel engine with a turbocharged air system with EGR, and model-reduction and model-inversion methods were used for simplicity of controller design [55]. More recently, ANN's are being developed by several researchers to predict the performance and emission for internal combustion engines for specific operating conditions focused on the experimentation of different fuel blends [56–58]. ANN's are also being used for onboard diagnosis and for mapping the emission- range area based on the traffic situation [59]. Because they can be used only for specific operating conditions, ANN is categorized as empirical modeling. However, they can assist engine control in various control techniques like predictive algorithms, supervisory control, or adaptive systems depending on the application.

Different prediction models were evaluated, which include multi-order filter techniques to process the data acquired. Controller types like Fuzzy, feed-forward, flatness-based, PID, and the combination of either a few or all of these controller types are discussed in detail. Their implementation depends on both the complexity of the analysis and the targeted simplicity which results in faster processing and decision time for actuation. The use of advanced techniques like ANN and its application in engine development to train these models and their calibration is also discussed. Yap et al. [60], utilized an optimization layer-by-layer (OLL) network as a supervised feed-forward learning algorithm, like the backpropagation, but OLL was proven to have a faster computation time. The architecture of OLL is shown in Fig. 8. This network consists of three layers. All neurons in the input layer are connected to all neurons in the hidden layer with weights W_{hi}. All hidden neurons are connected to all output neurons in the output layer with weights V_{oh}.

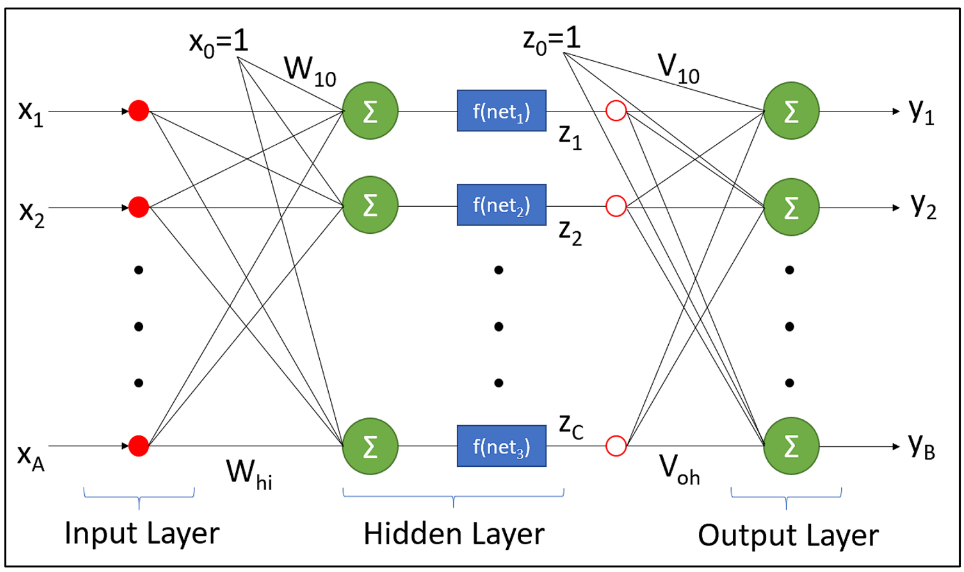

Fig. 8 Architecture of OLL in a layer by layer optimization

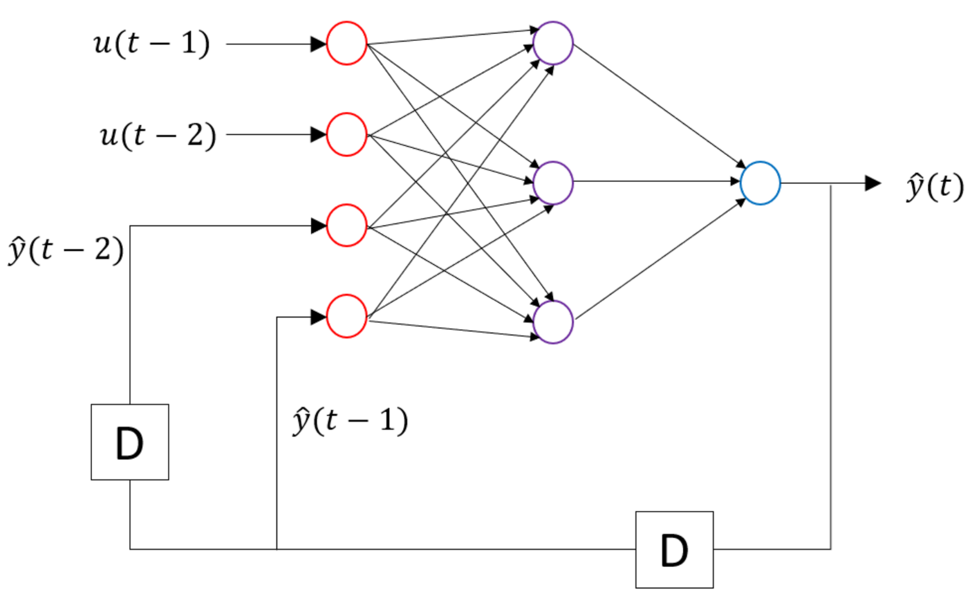

Fig. 9 Structure of NOE RNN used in virtual sensors

Recurrent neural network (RNN) models possess the advantage of having the dynamic behavior of the controlled system being manipulated by a simulated environment. Figure 9 shows the scheme of the RNN model used for virtual sensors where yˆand u are output and control input, respectively. These RNNs are developed from static multi-layered perception feed-forward networks. To introduce the dynamic effect, feedforward connections are added among the neurons. The control structure described here is referred to as a nonlinear output error (NOE) model. Training and test data sets have been derived from experimental data and measured on a compact commercial engine during engine transients by imposing throttle and load perturbations. To enhance RNN generalization, the input variables have been uncorrelated by perturbing the fuel injection around the stoichiometric amount.

4 Recent Engine Control Strategies

During the last few years, new technologies have been added as a result of new stringent actions and global standards set by a variety of organizations. Consequently, significant work has been done to increase the accuracy of prediction models, controller design and optimization, and to validate the different driving cycles practiced globally. Controller robustness and stability depends on the method of identifying control variables and plant states. These variables can be a sensor output or a model output based on the methods discussed earlier in combustion modeling. This section discusses a few approaches made in the development of modern diesel engines with advanced integrated systems to enhance efficiency and reduce emissions. Following are the challenges that are covered in this article:

a. Accurate prediction models
b. Controller design and optimization techniques
c. Controller robustness and stability strategies
d. Verification and validation through globally-practiced driving cycles

Air-path control in the EGR and Turbo equipped engines plays an important role in optimized fuel and NO_x control. In 2015, Min et al. [61] proposed an air-path model for a light-duty diesel engine with duel EGR-VGT to predict the unmeasurable states in-cylinder such as mass exchange traces and temperature. State estimation was done using the Least Square Optimization method and introduced a time constant for temperature and a transport delay to achieve the temperature estimation within 5% error and fuel mass flow accuracy up to three decimals. Another approach was made using the carbon dioxide (CO_2) based air-path model to evaluate the effectiveness of EGR under the emission constraints. This model required a physical sensor to measure oxygen (O_2) and was lacking the physical models for each subsystem [62]. But neither Min et al.. nor Tan et al. estimated NO_x or proposed any active NO_x control strategies. Wang et al. proposed a multi-input multi-output (MIMO) state feedback controller for multiple fuel injection pulses based on the pressure-based air-path model data taken from an engine map. The controller showed the guaranteed stability and shorter settling time for the experiment object, but this cannot be used as a generic solution due to a lack of physical models for EGR and VGT [63].

System Identification methods are proven to help evaluate such complex models including complex subsystems. Neilsen et al. used the Hammerstein-Weiner model for system identification to develop a complex nonlinear system consisting of EGR and VGT together with the fuel injection system [64]. A nonlinear adaptive controller was developed to control the EGR which continuously estimates the cylinder states with respect to operating points based on the Hammerstein model converging the system into the optimal control points in the presence of a few disturbances in fuel flow and Turbo effect. Although it controls the EGR, there were no methods proposed to estimate the in-cylinder states like Pressure, AHRR, and NO_x prediction was not done to assist the feedback control. The transient model requires additional control strategies to reduce overshoot during the operating cycle. A gain scheduled feedback proportional-integral (PI) controller for EGR and VGT is proposed by Hong et al. [65] to schedule gains for managing non-linearity of diesel engine models with EGR and VGT during the transient operating cycle. Based on the air-path model, static gains were derived from a nonlinear relation between the EGR and VGT performed on the European Operating Points. With the new scheduling variables based on the intake and exhaust pressure instead of the valve positions, controller performance was enhanced by reducing the pressure overshoot from 64 to 12% for a step change. However, Gain Scheduling is a repetitive procedure thus makes it time-consuming.

Another approach taken by Yang et al. [66] evaluated air-path models with EGR, Turbo, and Electrical Turbo Assist (ETA) for the closed-loop controller. These models were obtained from the MATLAB system identification toolbox using the lookup tables and test data on the engine. A simple MIMO controller (PI) was designed for three inputs and three outputs. Its robustness was also checked for disturbances by introducing gain scheduling strategies for certain setpoints in operations. But this approach was truly based on the lookup tables; hence, any uncertainty may fail the model's fitness. An additional active disturbance rejection controller with an extended observer is needed for such error tracking and control [67]. These approaches that were based on only a feedback controller with the lack of estimated or measured cylinder states restrict the robustness of the controller. Accurate prediction of cylinder states and engine-out products based on detailed physical and chemical kinetics models are needed for advanced modern diesel engine control. Ease of controller design and model parametric reduction is required to deal with these complex systems that are the results of detailed models.

Nylén et al. [68] proposed a functional mock-up interface (FMI) to implement the workflow from linear local feedback controllers to non-linear global systems and vice versa to control the global systems. Tools like Modellica Dymola can be used for such model-based control and significant model reduction. This approach provides a guideline for dealing with the complex systems for its optimization and control. Feed-forward and model predictive control are promising techniques for controlling complex nonlinear systems because of their adaptability and enhanced controller performance. Better results were found in both error and rising- time improvements for a model including EGT and VGT derivations? based on lookup tables [69, 70]. Dahl et al. [71] proposed a model predictive controller (MPC) for a reduced system. It was based on the Nelder-Mead-Simplex Algorithm for obtaining the parameter and cost function vectors between linear local models and the ultimate nested global model. They used burnt gas fraction as a control unit of NO_x control instead of EGR and showed better results using MPC in terms of improved error estimation and control. Similar approaches with MPC and additional supervisory controllers including more constraints in the system show optimized results in for transient cycles except for the overshoots when the steps are changed [72]. A zero-vibration input shaping in the robotics approach in an open-loop feed-forward system for input shaping to compensate the undesired overshoots and sensitivity is proposed by Großbichler et al. [73]. They noted a significant reduction in NO_x for some of the defined ranges of the operating points with better uncertainty handling.

With an understanding that an accurate model with detailed local models having multiple degrees of freedom is needed for an engine control problem to solve efficiently, some of the additional techniques are needed to make the controller more stable, faster, and more adaptive. In 2016, Yamazaki et al. [74] developed a strategy for model-based control of diesel engines with multiple fuel injection schemes to predict accurate in-cylinder pressure and temperature and controlled it with the EGR disturbances. A physics-based detailed model with all subsystems was developed. A feedforward and a feedback controller to control main fuel injection timing showed good accuracy in controlling the peak pressure timing in a cylinder. It has been proven that higher degrees of freedom (DOF) for fuel injection strategies reduce the EO emissions significantly [75]. Another work by Yamazaki et al. on the premixed charge compression ignition (PCCI) diesel engine estimated the parameters in the cycle by cycle operation. A feedback (FB) controller derived from an inverse model of discretized combustion was implemented to control the targeted set points in-cylinder [76]. The simulation showed significant and fast-targeted control, but some delays occurred when the step inputs were changed. These delays were caused by the error and inaccurate tracking in the air-path model. To compensate for this, a two DOF feedforward and feedback controller was developed along with an anti-wind-up control method to reduce overshoots at step change. They called this additional controller a Feedback Error Learning (FEL) system.

Zhang et al. [77] proposed the use of a CMAC (Cerebellar Model Articulation Controller) as a feedforward (FF) controller that trains the FEL developed before in their previous work as mentioned here above. A comparison of the FF CMAC and FB controller model with the FF CMAC and FEL model demonstrated the advantages of CMAC with FEL. Response in CMAC and FB always delayed by one cycle. However, when used with the FEL, it is seen that after the learning phase of FEL from CMAC, there is no delay in reference tracking because of the learning from the CMAC. the training data coming from a sensor does have limitations regarding indirect measurements, especially in peak pressure measurements. Cylinder Pressure based control of diesel engine applications is explained by Willems et al. in 2018 [78]. With the additional DOFs involved, Yamazaki et al. applied their controller findings by including more systems like Turbo and EGR together for detailed air-path and fuel injection models [79–81]. Physical actuator delays affect the control scheme and its performance significantly. Zhang et al. developed a chattering-free sliding mode control for diesel engine air path system with actuator faults that reduces the effect of the faults with their prior knowledge that demands the Fault detection models [82]. Kerik et al. developed an MPC for the diesel engine air-path and extended the actuator delay for the steady-state errors, overshoots, and other noises. This MPC with prediction models and an extended observer embedded with actuator delay showed better response for a few operating points. That still needs to be validated for wider operating points range [83]. The versatility of these models is the next task in the to-do list for researchers and that enhanced versatility can be achieved by harmonizing the operating cycles for validation used in different parts of the world.

The environmental pollution control agencies/organizations around the world have set policies and strategies to achieve their targeted goals in the next few years. In the case of NO_x emission from heavy-duty vehicles, it is seen that the existing technology can control the EO emissions under thresholds for all operations except low speed and low load application (less than 25mph) [84]. It is necessary to control the formation itself rather than after-treatment because of the after-treatment light-off limitations. Techniques like cylinder deactivation and variable valve actuation are required to achieve these goals [85]. A detailed effort was made by Shaver et al. [86] to develop a control-oriented model of a diesel engine's gas exchange process, which captures the complete interaction of air handling system components and flow in a multi-cylinder diesel engine with VGT and cooled with EGR. Models were created using GT-Suite and test data was acquired using dSPACE from electronic control module (ECM) and validated for both steady and transient operations. This work led to the development of closed-loop control and estimation strategy for Miller cycle development which will ultimately leverage the capabilities of a variable valve actuation (VVA) system.

In-line with the previous work by Shaver et al., a nonlinear model-based controller was developed for combustion timing with respect to CAD and could achieve control of the SOC and intake oxygen mass fraction within the resolution of 1 CAD and 1% fraction respectively. The controller's stability was demonstrated through Lyapunov analysis, and the functionality was experimentally validated at multiple operating conditions [87]. However, this work required a model for VVA with EGR and VGT acting together, which was then developed by Guan, Wei et al., 2019. According to them, although the Miller cycle adversely affects carbon monoxide and unburned hydrocarbon emissions at a light load of 2.2 bar, mean effective pressure is accurately indicated. Combining the Miller cycle with a second intake valve opening strategy as the formation of a relatively hotter in-cylinder charge induced by the presence of internal exhaust gas recirculation led to a significant 82% reduction in soot emissions when compared with the baseline engine operation [47]. Also, the controller design and implementation strategies have been used with controllers like dSPACE DS1104 and experimental validation can is done to achieve near-zero accuracy [88]. The overall results demonstrated that advanced variable valve actuation–based combustion control strategies can control the exhaust gas temperature and engine-out emissions at low engine loads.

as well as improve upon the fuel conversion efficiency and total fluid consumption at high engine loads, potentially reducing the engine operational costs. Based on these findings, Miller Cycle Development and Control is a future research gap for Diesel Engine development and can be optimized for better performance and emission control. Table 4 shows the recent strategies that are required for versatile control of a modern diesel engine. It includes the comparison of different controlling strategies based on control variables, controller stability, adaptability, robustness, and its optimization. These models and corresponding controller strategies can be implemented as a separate plugin device/s on existing systems as.

well [89].

5 Summary

This review provides a brief history of Diesel Engine development as well as the emission control strategies that have evolved over the last few decades. Figure 10 illustrates the percentage contribution of the literature since 1930 that was reviewed for this article. The increase in the number of on-road vehicles led to the establishment of the EPA which introduced stringent emission control norms and the need to minimize tailpipe emissions. Efforts taken by various researchers and car manufacturers to comply with these mandates are discussed in the second section. Finally, the complexity of engine control algorithms due to various technologies and the need for diesel engine combustion modeling is discussed in detail. The three major types of modeling methods and the respective work done by researchers using each method are investigated and provide insight into the strengths and limitations of each method.

Empirical and phenomenological models have several disadvantages because they are limited to specific test cases and computational efforts respectively, which largely eliminates their use for the generic purpose. The current state of the art for these models set a scope for a more detailed study of the combustion phenomenon by understanding and developing multi-phase combustion models. Physics-based combustion models are best suited to meet controller design requirements considering new technologies like EGR and VVA. Various attempts are being made to develop more generic and realistic models for current engine technologies that consider the maximum number of transient variables. A potential to develop the high-fidelity Miller cycle model for combustion phasing is also proposed. This model can include more engine parameters to achieve higher resolution with respect to CAD for performance and emission control with a maximum accuracy of more than 96%.

There is a potential to develop ANNs and machine-learning-based techniques for sub-models/models, which can interact with each other and make them more generic and adaptive. Few researchers have developed a structure of the sensor dynamics models consisting of dead time and a first order-low-pass filter with a certain response time. These sensor-dynamic phenomenological algorithms have a significant impact on comparisons of virtual sensors with physical sensors. Especially this is true, when rapid transients and various engine operating region response times vary, potentially leading to errors in sensor comparisons. To reduce these errors, a rapid NO_x-measurement in the proximity of an exhaust manifold is necessary.

During the last decade, various environmental protection organizations around the world revised their clean transportation policies and the threshold for emissions. Surveys have been done on different technologies involved in achieving

Table 4 Recent diesel engine control strategies

Ref. No./ Author	Controller type/ Strategy	Control Variables	Adaptive	Delay Reduction	Predictor	Optimization	Stability Analysis	Gain Scheduling	Extended Observer	Disturbance rejection	Actuator Delay Control
[42] Guzzella et al.	Self-tuning PID, LQG	2	✓	✓	✓			✓			
[51] Cao et al.	Fuzzy logic, PID	2	✓								
[52] Wahlstrom et al.	PID, non-linear	2	✓					✓			
[53] Arnold et al.	PID, Fuzzy multivariable	2	✓		✓						
[54] Dabo et al.	Dynamic FB PI	3	✓								
[55] Kotman et al.	Flatness based FF	2									
[60] Yap et al.	FF, OLL	2	✓								
[61] Min et al.	Least Square Optimization for State estimation	2	✓	✓		✓					
[63] Lau et al.	State FB	2			✓		✓				
[64] Nielson et al.	Non-linear, Hammerstein model	2	✓			✓					
[65] Hong et al.	FB PI	2	✓				✓	✓			
[66] Yang et al.	FB PI	3	✓	✓				✓			
[67] Chen et al.	FB PI	3	✓	✓			✓	✓	✓	✓	
[68] Nylen et al.	FF, MPC	3	✓	✓	✓	✓					
[71] Dahl et al.	MPC, Nelder Mead Simplex Method	3	✓		✓	✓		✓		✓	
[72] Karim et al.	Supervised Control, MPC	3	✓		✓	✓			✓		
[73] Großbichler et al.	FF	3	✓	✓	✓	✓	✓		✓	✓	
[74] Ikemura et al.	FF & FB	3	✓	✓	✓	✓	✓	✓	✓	✓	
[76] Hirata et al.	FB with FEL	3	✓	✓	✓	✓		✓	✓	✓	
[77] Zhang et al.	CMAC, FF	3	✓	✓	✓	✓	✓	✓	✓	✓	
[82] Zhang et al.	Chattering free sliding mode control	3	✓	✓	✓	✓	✓	✓	✓	✓	✓
[83] Kekik et al.	MPC	3	✓	✓	✓	✓	✓	✓	✓	✓	✓

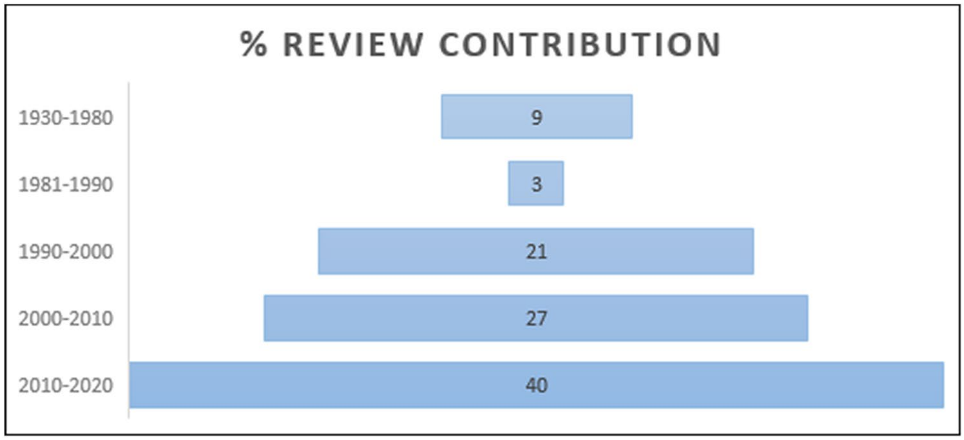

Fig. 10 % Review contribution during the last few decades

the targets set by these organizations. A few approaches are discussed in the last section based on the controller design and development that emphasizes precise and stable engine control. Accurate cylinder state estimation techniques are needed to achieve these stringent goals for controller development because of the limitation in state measurements with the physical sensors. Another survey from international council for clean transport (ICCT) concluded that more strategies are needed to deal with engine control during the low load operating points. Certain techniques like Cylinder de-Activation and VVA are proven to be effective for these requirements. In conclusion, precise in-cylinder state estimations, robust controllers, and a targeted and harmonized operating cycle will guide the future development in Diesel Engine Control.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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