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Chapter 9: AI-Enhanced Energy Efficiency and Engine Performance Optimization

9.1. Introduction

The high carbon footprint of the transportation sector has prompted the growing introduction of stricter emission regulations and more demanding customer expectations with regards to fuel economy. Nevertheless, the evolution in powertrain architectures and control strategies has not yet been able to follow a similar pace in order to ensure that such regulations are met, nor to achieve the commitment to net-zero CO2 emissions by 2050. As such, the energy efficiency of the powertrain should continue to be analyzed and improved, while also accounting for the additional acting constraints on emissions, performance and drivability. Besides supporting the minimization planning of powertrain demonstrators, the global methodology contributes to define data-driven control strategies targeting engine performance optimization through energy efficiency enhancement.

The different metrics applying to the powertrain and engine, namely thermal management optimization, heat recovery maximization, fuel economy increase as well as emissions reduction, play already a crucial role in their control. Nevertheless, the full potential of their mutual interactions responsible for performance enhancement has not yet been entirely exploited. Dynamic actuators coordination banks on the fact that at least two actuators exist for the same powertrain's degrees of freedom to manage, in particular when a control strategy harnesses the predictive character of the powertrain model: turbocharger boost pressure and electrical torque demand, idle-speed control—trades-off driving comfort and fuel saving, dynamic aggressiveness—balances fuel economy and drivability.

9.2. Fundamentals of Engine Efficiency

Thermodynamic Efficiency

Internal combustion engine (ICE) efficiency derives from two sources: low entropy generation during the combustion process and the mechanical operation of the engine. These are described by the efficiency with which the chemical energy of fuel is converted to heat or thermal efficiency, and the thermal-to-mechanical conversion efficiency, respectively. Both combine to describe the concept of thermodynamic efficiency; the maximization of which is the goal of physical modeling and generally accepted best practice before improvisation. Nonetheless, a client-driven vehicle can never be expected to operate under perfect conditions [1]. Thus engine performance metrics must address the areas that dilate its ideal characteristics. The true challenge of boosting engine efficiency lies in achieving its optimum at the widest scope with the least collateral damage, as assessed against an expansive list of performance metrics, rather than concentrating single efforts on a particular improvement.

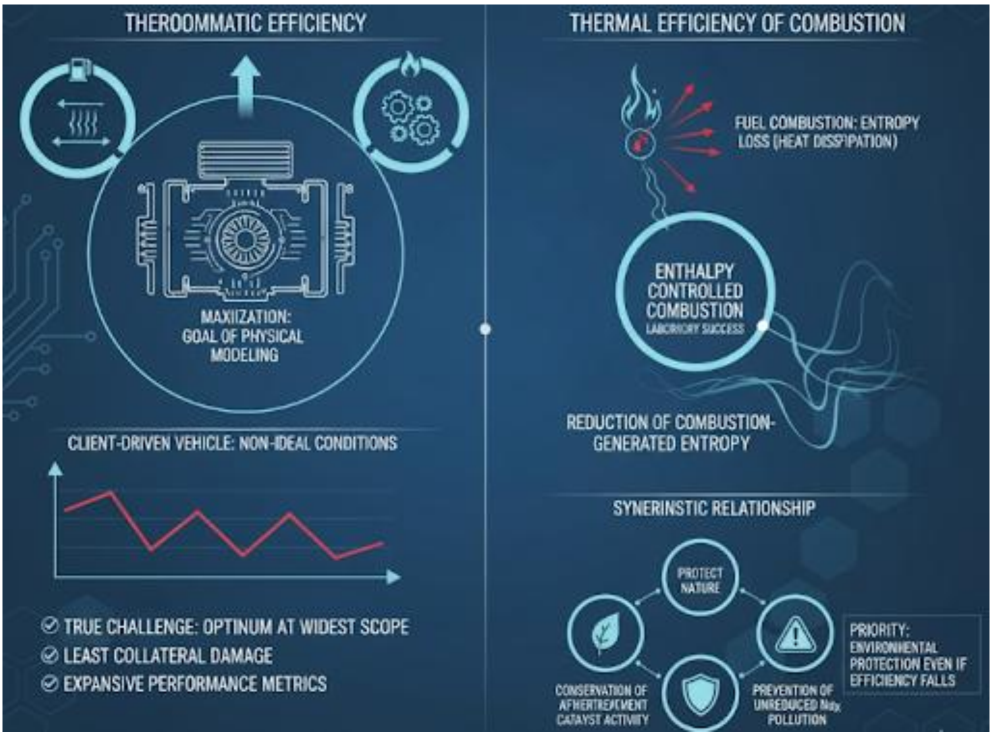

Fig 9 . 1 : Thermodynamic Efficiency and Combustion Optimization in ICEs

Thermal Efficiency of Combustion

Fuel combustion is not a perfect process. During combustion a percentage of the chemical energy is lost to entropy as heat is liberated. Some of this heat is used in the thermal-to-mechanical energy conversion, but the rest is further dissipated. This cleanest of all internal combustion products moreover has little thermodynamic value and is an ideal vehicle for Enthalpy Controlled Combustion – the only combustion process to have achieved laboratory success. Reduction of combustion-generated entropy is the road to increasing thermal efficiency, and this target can be artistic. A fine balance must be achieved between combustion efficiency and other powertrain operating conditions with a synergistic rather than antagonistic relationship exploited: conservation of exhaust aftertreatment catalyst activity is imperative to protect nature even when combustion efficiency scores fall, and thus the prevention of unreduced NOx pollution takes precedence should boiling the catalyst become essential.

9.2.1. Key Principles of Engine Performance Optimization

Powertrain optimization for enhanced fuel economy and low pollutant emissions has been the subject of extensive research over the past decades. Thermodynamic cycle analysis highlights the key principles: the Carnot efficiency establishes the upper bound for an engine's fuel efficiency, while the combustion and volumetric efficiencies represent the fraction of the fuel's chemical energy available as power. Reducing the friction losses is essential for enhancing the overall efficiency, which has presented a trade-off with the heat management over the engine cycle [1,2]. Experimental investigations in automotive and aero-propulsive engines can be leveraged to establish a detailed baseline of engine performance.

For automotive engines, the temperature and pressure distributions along the engine do not follow constant Air/Fuel ratios because of the change in fuel composition with operating conditions – such as with bio-fuels (butanol blends) and syn-fuels (Fischer Tropf synthesis) – that have shown to increase NOx emissions in the transient stage. Further studies have proposed modifications in the aftertreatment system to redistribute the soot-NOx trade-off during the Worldwide harmonized Light vehicles Test Cycle (WLTC) and the Federal Test Procedure (FTP), accounting for the vehicle's life cycle for the installation of the pollution after-treatments' pollutants. Experimental investigations at partially and fully electrified conditions provide a deeper understanding of the limitations of an automotive engine during electrical operation: it requires auxiliary storage devices for complete electrification and a rotating mass such as a flywheel when partially electrified to keep electrical consumption at low levels.

9.3. Artificial Intelligence in Powertrain Management

Artificial Intelligence is applied to three major areas of powertrain management: data acquisition and sensor fusion, modeling and simulation to enable predictive control, and real-time optimization algorithms.

Data acquisition generally relies on sensors distributed throughout the vehicle. Sensor fusion is used to match the sensor data with the application needs to produce high-quality information. Sensor data preprocessing and synchronization are crucial to ensure data quality for the subsequent model. Special attention is required in accordance with the sensors' latency and reliability. Erroneous readings can be produced by sensor degradation, malfunction, and calibration errors; hence, uncertainty handling is a necessary part of the process. Preprocessing steps can be set to augment the data with high-quality information, which can mitigate some issues.

Three main training regimes are applied to model development: physics-informed methods, data-driven approaches, and scenario generation. Physics-informed models use physical knowledge to minimize the data requirements and ensure the accuracy of the results. Data-driven models focus on the optimization of the control strategy from the sensory data. Despite the aforementioned fusion, it might be required to exchange high volumes of data at low latency for sensitive controllers. A solution can be to use an additional agent to provide high-bandwidth training by reconfiguring the powertrain to explore particular operation conditions [3-5]. Data-driven models can also complement physics-informed ones, especially for the less-reliable scenarios defined in the Others training regime, enabling user-defined additional constraints.

9.3.1. Data Acquisition and Sensor Fusion

Safety performance requirements impose rigorous constraints on data certainty, quality, and integrity for AI-enabled powertrains that are frequently absent in conventional engines and vehicles. Sensors must therefore be carefully selected such that the level of uncertainty introduced into the AI model output is assured to remain bounded throughout the operational envelope, and preferably within regulatory limits. Transmission delays, drifts, jitter, and dropouts detected at the output of the sensor processing stages should be addressed through appropriate filtering, compensation, and buffering. Unreliable sensor data can either be masked by redundancy or compensated for through predictive schemes based on other inputs. Other strategies include data fusion, outlier detection and acknowledgement, confirmation synchronisation, and advanced state estimation algorithms algorithms but these place added burdens on the computation hardware and require careful design and validation. As a first step, a classical Kalman filter may be sufficient to provide an acceptable mode of operation. For other algorithms, failure prediction and detection mechanisms should be employed to identify and replace untrustworthy signals in real time.

Fusion of information from multiple sensors. Important processing functions for predictive control research are sensor simulation and sensor data fusion, and both have thus far followed different parallel paths. Sensor fusion combines measurements from numerous sources to estimate motion state variables with potentially more accuracy than any single sensor. The process fuses information from a range of sensors operating on different physical phenomena, and combines different data types such as numeric signals, logical statuses, and error descriptions. As part of the fusion process, biases may be removed and redundancy tolerated, resulting in a trimmed error probability. The Gaussian filters that achieve these properties are simple to implement but assume an extensive class of distributions, which match many situations encountered in the real world. Among AI approaches, fuzzy logic is a well developed and popular tool especially for high level decision making, as it is naturally able to deal with the uncertainties present in real-world systems. More recent sensor fusion techniques have extended expert systems such that they can also make predictions by fusing age-balanced information stored in memory.

9.3.2. Modeling and Simulation for Predictive Control

Compatible engine control strategies deliver enhanced power and emissions performance when data-supported predictive models are deployed in closed-loop operation. Physics-informed models remain the most robust modeling approach for emerging applications where data are limited, but lifecycle considerations often require multiple operating points to be evaluated in a single simulation.

Physics-informed engine models for predictive control should be sufficiently flexible to accommodate novel optimization targets while remaining computationally efficient to enable real-time controller operation. A multilayer feedforward neural network has recently been applied to predictive engine control, demonstrating acceptable performance with the computational demands of the problem formulation. Training of data-driven models is often intertwined with the feedback control process, enabling rapid generation of a physics-informed surrogate model designed specifically for the task at hand.

Data-supported control strategies derived from reinforcement learning offer the potential to seek control solutions globally over an extended operating envelope. Data-driven equivalents of classical control concepts including bang-bang, model predictive, fuzzy, PID, and dynamic programming control strategies have recently been defined. Multi-agent reinforcement learning can accommodate communications-intensive predictive control of a group of redundant and coordinated systems, and deployable runtime layers such as CAPTCHA and Cylindrical-Shape Lens can simplify the human-interaction display.

9.3.3. Real-Time Optimization Algorithms

Real-time optimization encompasses the generation and execution of control commands that balance competing objectives while satisfying active constraints. Such requirements are typically met through either predictive control or reinforcement-learning paradigms. While predictive approaches determine control actions that best follow the prediction horizon trajectory, reinforcement-learning-infused methods often operate in a suboptimal manner but exhibit good generalization capabilities. The success of both paradigms relies on an optimizer that converges in a sufficiently short time to a corresponding solution. Furthermore, given that control actuators are invariably finite-rate and imperfect, the stability of the system under control must be guaranteed.

Predictive control, specifically Model Predictive Control (MPC), is the most common optimization approach deployed in combination with an internal model of the system under control [6,7]. The internal model may be physics-based for trusted scenarios, data-driven and trained using closed-loop operation data for untrusted conditions, or even incorporate elements of both worlds in a physics-informed manner. Conversely, the formulation of the reinforcement-learning problem must be consistent with the underlying mechanics in order to provide a modicum of performance, and control latency is implicitly defined by the training setup.

In addition to predictive and reinforcement-learning paradigms, several other real-time control methods have been proposed for powertrain applications. These range from simpler heuristic formulations and traditional control strategies to gradient ascent and other AI-based techniques. An important aspect in any of these formulations is the role of operation-point-specific information. To ensure rapid convergence of the underlying algorithms, it is commony assumed that the near-real-time control command should lie in the vicinity of the appropriate solution, which is typically achieved through the intelligent interpolation of precomputed data.

9.4. Energy Efficiency Metrics and Evaluation

Thermal energy management is advantageous for several reasons. Good thermal integration of the various cooling circuits increases the overall heating/cooling capacity at low cost. Latent heat storage, such as battery units with phase-changing materials, provides thermal buffering to improve the aging of energy consumers and generators.

Thermal energy routing and distribution architectures that allow heating/cooling on-demand are preferable. Waste heat from fuel cells and PEM fuel-stack-type batteries, for instance, can be stored and reused in times of high demand.

Fuel economy and emission levels during standard operation are critical for the market introduction of hybrid propulsion systems. A combination of cyclic mass emissions metrics, such as the WLTC and FTP, must be strictly satisfied. Nox emissions and soot generation during WLTC/FTP should be balanced. Furthermore, the lifecycle of the ultra-low emission concept must minimize the environmental impact of the entire vehicle concept, not just the tailpipe operation [2,8-10].

The presence of a high-voltage hybrid architecture allows energy to be routed from any producer to any consumer or even stored in a battery or supercapacitor. However, the characteristics of the components must be respected. Supercapacitors can provide high bursts of energy, but are not able to store energy for long periods of time. Batteries, on the other hand, present the inverse behavior. For energy routing to be reliable, DC-DC converters must be present. The energy routing strategy must minimize civil engineering costs and energy losses. Simulation of the energy architecture with selected boundary conditions helps to understand the best routing strategy.

9.4.1. Thermal Management and Heat Recovery

Thermal efficiency can be effectively improved via proper thermal management and waste heat recovery technologies. Cooling circuits must ensure that both the engine and the electrically driven units operate at their respective optimal temperatures during normal operating conditions. Additionally, the engine cooling circuit must incorporate a variable heat exchanger that allows the return of sufficiently heated coolant to the cabin in winter. Moreover, other circuits (e.g., battery, oil) must be matched to the need for heat consumption or production based on the operating demand. With a large-temperature span in summer, the possibility of integrating a phase-change heat exchanger that is kept in a dormant state can further minimize parasitic losses.

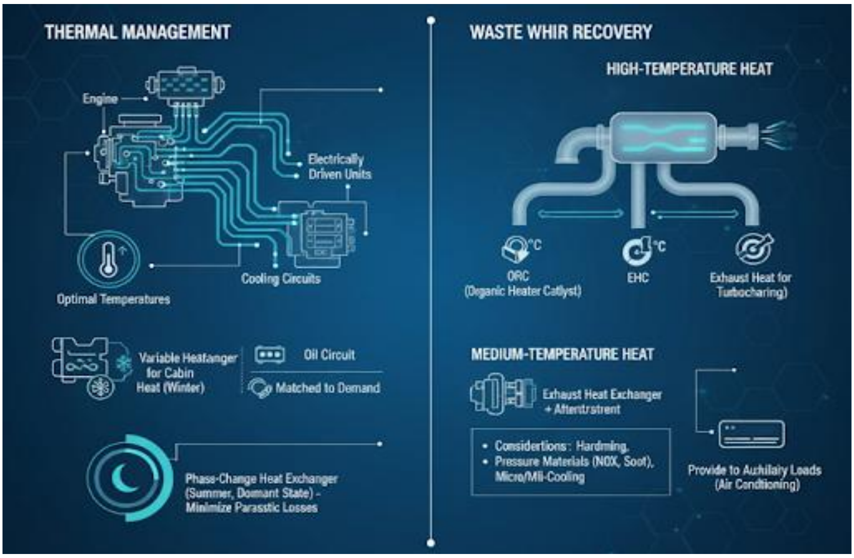

Fig 9 . 2 : Improving Thermal Efficiency: Management & Waste Heat Recovery

The use of waste heat can also improve energy efficiency and can be categorized as using high-temperature heat, medium-temperature heat, or low-temperature heat. In addition to integrating dedicated waste heat recovery systems (e.g., ORC, EHC), combination with other circuits must also be addressed for improved effectiveness. Among different uses, the recovery of exhaust heat for turbocharging or the coupling of an exhaust heat exchanger with the aftertreatment system can offer high potential. However, these solutions must consider not only the level of hardening but also the increase of overall pressure losses and the materials involved on NOx and soot emissions. The implementation of micro/mili-cooling of the aftertreatment system also deserves further attention. The remaining low-temperature heat can be provided to auxiliary loads such as air conditioning.

9.4.2. Fuel Economy and Emissions Reduction

Fuel economy and emission levels during real-world operation are key attributes of installed powertrains. Fuel consumption is not only the dominant operational cost, but also impacts pollutant formation and, consequently, regulating measures in many world regions. While, under certain driving conditions, a compromise between NOx and soot emissions can be achieved, improved fuel economy and reduced emissions are considered in a lifecycle context.

Regulatory cycles for development and validation of powertrain systems are often based on standardized cycles like the Worldwide Harmonised Light-duty Vehicles Test Cycle (WLTC) or the Federal Test Procedure (FTP) for passenger cars. Considering the underlying principles of such defined cycles, the direct implementation of both Battery Energy Storage (BES) and Combined Supercapacitor–Battery Energy Storage (CSBES) systems would result in an unchanged energy demand compared to their internal combustion engine (ICE)-only counterpart [1,11-12]. Consequently, the same amount of fuel should be consumed. In practice, however, the chosen approach provides benefits in the form of energetic support and associated reduced ICE operation time, leading to smaller total fuel consumption and a mitigation of harmful exhaust species.

9.4.3. Electrical Architecture and Energy Storage Integration

Integration of supervisory powertrain control with enhanced electric architectures broadens operation and contributes to energy efficiency via strategic routing of energy between high-voltage (HV) and low-voltage (LV) power circuits. Complex Signal Processing considers the structure of supervisory powertrain control together with relevant actuators, such as high-voltage (HV) storages (typically batteries and/or supercapacitors) and DC-DC converters. The objective is to minimise external energy supply while satisfying engine functionality, emissions targets and user comfort.

HV-LV power-architecture integration enables the distribution of alternating current and direct current by integrated or closely related electric machines, energising dedicated or shared loads and permitting energy routing between LV and HV storages. Unlike traditional drivetrains, energy routing is a managed Supervisory signal and may involve unintentional power flow, e.g. driven-from battery with regenerative brake charging supercapacitors but not propelling vehicle. Generalised power routing properties are based on common points of the DC-LV and DC-HV circuits, unidirectional power flow through fusible devices and, for AC supplies, reciprocal power consumption.

The expected impact of electrical architecture and HIS is significant. Energy routing reduces energy consumption by minimizing the electromagnetic conversion losses and, if a Li-ion battery and supercapacitor are used, brings additional advantages: the Li-ion battery provides the daily tasks of the e-vehicle, while the supercapacitor covers the peaks of energy consumption, thus minimizing stress on the battery and increasing its life span. Nonetheless, the routes and quantum of energy exchanged should be managed: providing for too much flow may increase the energy consumption, due to the presence of the DC-DC converters, thus resulting in a negative impact on the vehicle productivity.

9.5. AI-Driven Control Strategies for Engine Performance

Electric components integrated into contemporary hybrid and electric vehicles can alleviate engine power requirements, notably during low-speed, low-load operation. This allows for increased engine thermal efficiency under partial load by means of downsizing, optimizing combustion for lowest fuel consumption or emissions, or even shutting down the engine altogether [13-15]. However, road load conditions and ancillary aside, the truly dynamic processes and cyclone work of the Puma-bladed turbines require active management. In a conventional Internal Combustion Engine, the turbocharger operates on a wasted waste from the engine, both turbine and compressor and valves and engines operating in dynamic equilibrium and presenting a dynamic surface rather than a kinetic picture.

Typically, the exhaust-boost-torque path bulks or gulfs across a hysteresis loop becoming surging during the braking-type condition and contributing most as the energy demand of the vehicle for its energetic form decreases towards zero. Even though today's aftertreatment systems are aimed at a nevertheless constant engine exhaust temperature and/or species composition, they integrate operational delays of several seconds or even longer, and grow gradually forward or backward towards zero. Their combination thus requires a coordinated control between the two sides of the engine operating region in order to shorten the delay without exceeding the present limit for surge. Otherwise, the advanced aftertreatment modes—most certainly all in all modes of sensitive species such as Soot and/or NOx—designed reducing such particles on their age-respectively far-forward closure behavior towards finally kill a use-condition be virtually unused during pure-engine braking type operations.

9.5.1. Dynamic Boost and Torque Allocation

Dynamic boost and torque allocation encompass a broad class of optimization problems, where the objective is to minimize operations time while fulfilling encapsulated target variables within a specified range, subject to all system constraints as defined by the control design. Potential applications include dynamic torque allocation of hybrid electric powertrains, torque coordination between ICE and electric drivetrains, throttle dominance during EV operation, and turbocharger operation. In these scenarios, powertrain components are interchangeably active or stand-by, and the combination of operating conditions amongst both power-producing units needs to be dynamically optimized. An example is enabling an electric aftertreatment heater only when the exhaust heat content is insufficient for satisfactory NOx conversion, such that fuel economy is maximized without compromising namable emissions; this can be further extended to supercapacitor deployment.

An additional dimension of optimization comes from the consideration of actuator wear over their lifetime. For any actuator-controlled subsystem exposed to repetitive actuation (particularly at low speed), extreme rapid changes in actuator command may lead to increased wear. Such wearing aspects are particularly prevalent in idle-stop detection (where a car is stationed for a long time) and low-speed regeneration (where a turbocharger operates near the surge region). Combined with reduced convergence times in such use-cases, hysteresis effects may be desirable for the deployment conditions to take effect. Hence, both the reactivation detection point and the deactivation recovery strategy may warrant optimization.

9.5.2. Adaptive Idle and Shutdown Policies

The engine idle and shutdown modes present significant energy and emissions savings opportunities. The idle state is exceptionally delicate concerning NOx and soot emissions, as excessive or unstable production increases environmental burden without satisfying operational requirements. These contradictory demands can also lead to engine wear, as thermal cycles deplete lubrication while unburned fuel enters the oil circuit. Idle fuel consumption can amount to an impressive tens of percent of the fuel consumed during the complete engine cycle, using FTT data for direct-plug vehicles; its replacement by an electric heater can yield substantial benefits. One possible way to reduce idle wear is the use of a standalone very-low-idle electric unit; however, this entails additional costs. The hysteresis nature of the idle state detection can be exploited to save wear and fuel by adapting the hysteresis intervals and pilot-igniting during maintained-drain activations. Eljudill et al. proposed to combine such hysteresis with thermal models to allow efficient and safe shutdown periods for direct-plug and heating-plugin vehicles, with the fuel saved by an idle mode sometimes exceeding the startup toll.

An ML classifier labeled the requested wheel torque for data segments. Such automatic partitioning can be exploited to evaluate and fine-tune hysteresis parameters governing an adaptive dual-ignition-wall-contact strategy, allowing the bypassing of the energy-demanding part of the catalyst; all without labelling the FC and NOx detours embedded in a classical training. Jensen's methodology estimates stable wheel-load areas for the direct-plug part of the FTP, identifying shutdowns during which the external conditions allow safe ignition neglect. Quantifying the fuel saved by such neglection for every shutdown and setting static or strategic detection rules with hysteresis or penalty can be done for every driving-cycle database, and achieved savings included in the overall-drivability track evaluation.

9.5.3. Turbocharger and Aftertreatment Coordination

Runtime assessment of target inputs for boost pressure controllers and associated control laws are similarly useful for combining turbo-boosting with aftertreatment technologies. First, surge limits can be enforced by adapting the actuator-coordination algorithm so that the turbo cannot demand more airflow than is allowable under the current engine-speed setting. Second, descents into shutdown mode can be detected by monitoring the durations for which the valve-positioning actuator is set to zero and the gas-efficiency controller is staged down. Once these engine conditions are sensed, before-function hysteresis is invoked to mitigate overflow of the catalytic aftertreatment. Commanded bypassing of the exhaust aftertreatment through the continuation of exhausted-gas cooling serves to prevent wetting of the catalyst. Conversely, recovery from shutdown mode can be affected following a single recovered engine crank, which moderates the risk of catalyst- and exhaust-turbine-overheating damage. Parameterization of this scheme enables both conservatively low design of the bypassing set points and correct reduction of NOx emissions during the stage-two periods of the World Light-Duty Test Cycle.

Runtime assessment of turbo-boost demand is additionally beneficial for aged aftertreatment. In this regard, historical trends of the catalyst's light-off temperature are tracked through integration of an order-reduced gas-kinetics model into the ensemble of operating conditions. Disk-based thrust controllers that reverse the normal direction of wheel rotation as a function of measured turbo-boost pressure are trivially concluded.

9.6. Safety, Reliability, and Cyber-Physical Considerations

Considering their sensitivity, reliability, and security, and the potential safety implications of an AI powertrain, ensuring the accuracy, fault tolerance, resilience, and protection of the control algorithm against malicious attacks is paramount.

The need for data integrity and algorithm reliability is typically addressed through monitoring, validation, and redundancy mechanisms. Monitoring functional deviations by comparing state estimates against the values predicted by physics-informed models can be combined with a model softening stage to identify model confidence. Hardware redundancy, powered by a constant safety-first design philosophy, can be crucial in ensuring successful operation and degradation mitigation, as exemplified by the dual pointed-nose and gimbal-less main antennas on the Hubble Space Telescope. These measures do not preclude the development of additional fail-safe modes, such as disabling the powertrain AI control logic without isolating electrical components in the event of battery failure.

The powertrain AI can be designed to address some sources of operational variability, including lingering actuator defects, but cannot be expected to be robust under all contingencies. These considerations imply that AI methods for drive experimentation, testing, tuning, and validation should accommodate reduced operation fidelity. The absence of wind, precipitation, and/or snow typically elevates vehicle range, while high temperatures often reduce battery and thermal management energy consumption. Profiled adaptation of AI model-parameters to environmental conditions can compensate for broader physical influences, e.g., altitude, street-type, season, and weather variations. The management of seasonal profile deviations, such as tire-wear and catalyst aging, can further enhance operational performance.

9.6.1. Data Integrity and Fault Tolerance

Data Integrity and Fault Tolerance: Data quality affects control and decision-making. Validation of inputs in time-sensitive operations enhances reliability. Data redundancy minimizes risks and maintains functionality in fault scenarios. Fail-safe modes mitigate and manage unforeseen faults. Anomaly detection identifies data aberrations. Data quality is essential for every control and decision-making task across AI powertrains. Quality assurance measures must be in place, including data validation, redundancy, monitoring, and anomaly detection.

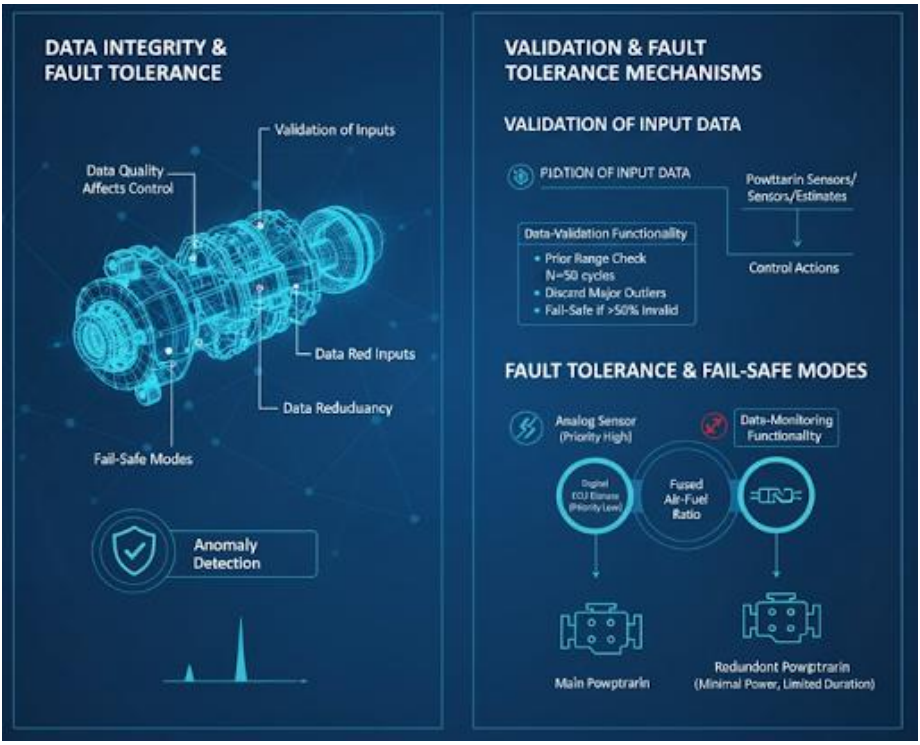

Fig 9 . 3 : Data Integrity & Fault Tolerance for AI Powertrains

Validation of Input Data

In typical operation, information flows from various powertrain sensors and estimates (temperature, exhaust pressure, torque demand, etc.) to predictor/decision modules that lead to control actions. In time-sensitive tasks, such as PID control of the turbocharger or aftertreatment system, the integrity of input data is vital. A sudden spike (more than three standard deviations above or below the mean) can trigger wildly incorrect responses. These control modules should therefore have the following data-validation functionality. For each input, the estimate should be validated against a prior range for that input during the past N (N = 50) cycles. The module checks its range and discards the major outlier. In the event that more than 50% of sensors become invalid, the whole module switches to fail-safe operation.

Fault Tolerance and Fail-Safe Modes

Data redundancy can provide fault tolerance. Analog sensors and digital-ECU-based estimates for the same variables (e.g., air–fuel ratio) can be fused together. When one source is unavailable, the other can be utilized. Each sensor is also assigned a priority: for instance, during an idle event, the air–fuel ratio does not vary with torque request and the digital-ECU-based value may become unreliable and be replaced by the analog value. Data-monitoring functionality detects when a variable ceases to take valid values, and that variable is then not utilized in subsequent operations. To further improve fault tolerance, a redundant powertrain can be included to maintain a minimal-level power output for a limited duration and allow the main powertrain to recharge.

9.6.2. Robustness under Operational Variability

Models tend to drift during the operation phase due to component ageing effects, sensor drift, and unmodeled phenomena. As a result, AI algorithms recognizing control actions that should be given under considered ambient conditions may become less accurate. Furthermore, factors such as weather conditions (i.e., rain and snow) or altitude variations may alter the relationships learned via AI, given their stochastic nature. Addressing these concerns may become crucial to avoid e.g., the over-inhibiting of aftertreatment ovens in winter or a mismanaged turbo boost at high-altitude. Some techniques have been designed to counteract these issues.

Weather-based algorithm switching is a common solution adopted in commercial products. A more elegant, albeit heavyweight, approach is to use a weather or altitude state dimension within the model, although it is rarely seen in practice. The main intuition behind adopting the latter is that any control action, especially mapping values of an unobserved causal variable, implicitly accounts for unobserved variables that would affect the mapping if known. A correction term therefore takes care of these influences, provided enough data is available in the learning stage. In this way, the algorithm should be able to recognize different weather or altitude conditions and generalize the policy accordingly.

Data logging and kernel regression can help manage model drift, e.g., a chemical species in an emission map may become less accurate with an aged scr catalyst. Moreover, abnormal situations, such as a fault on the Ammonium Urea Supply Unit or a particularly sulphated catalyst, may also lead the mapping to predict extremely low or high values; unexpected events can thus be handled too. State-aware models can partially help counteract the development of costly increment sides too.

9.6.3. Security and Privacy in AI Powertrains

Cyber-Physical Systems (CPS), such as those utilized in modern vehicles, are increasingly reliant on communication among processing units and engines to ensure seamless operation. Many of these components have direct access to communication channels, yet the implementation of security measures has not kept pace with their increasing capabilities and importance. The security of cps is defined as an agreement between the participating parties protecting the integrity, authenticity, and confidentiality of the exchanged data. It is vital for vehicle security to follow the safety enhancements applied in other domains, such as aerospace, to avoid cyber incidents like Trojan horses, denial of service, and spoofing attacks.

Different threat models can be defined depending on the development support open regions of the targeted components, and integrated systems can be attacked with the same techniques used against it. The components in which communication must be assured can be divided into two categories: the sensitive units, whose messages must be protected because they control the vehicle or the motion of the vehicle, and the other units, which are responsible for the execution of commands of the first category. The goal of such security measures is to make the detection of vulnerabilities as easy as possible so the system can be protected from external unwanted access. Functionality must not also be considered an optional feature; on the contrary, it's another resource used to determine additional actors in the cyber confession that could be used to gain an accolade to the secure units through various means [7-9]. Such integrated features take the form of continuously operating services without direct interaction with the car receiver unit. Most of the present-day cars share all sensor parameters with leased vehicle centers, granting detection ease, redundancy, and lower costs to the hackers.

9.7. Conclusion

AI-Enhanced Energy Efficiency and Engine Performance Optimization concludes with a summary of principal insights and considerations for the practical implementation of the methodologies. Research and literature that address the available information gaps are highlighted, directing future work toward improving the efficacy of the data management, modelling, control, and decision-making components of powertrain systems.

The system-level integration of AI technology has the potential to significantly improve energy economy and exhaust emissions of automotive engines—yet little published evidence supports this assertion. Insufficient, incomplete, and low-quality AI training data undermine the performance of algorithms. Established methodologies from control engineering, operational safety, and cyber-physical-system design have not been coalesced to prepare AI for deployment in the demanding setting of real-time powertrain operation, and the impact of AI technology on system decisions remains poorly understood. Prior work has presented AME-level safety and reliability requirements, but these must be recast in a manner amenable to practical implementation.

To address these and other shortcomings, the current review examined the objectives and AI-enhanced strategies used to optimise electric and thermal management, energy recovery, and mode-specific performance of automotive engines. Improvements in fuel economy, emissions, and pollution impact were targeted, addressed, and symbiotically combined in the context of the well-to-wheel life-cycle perspective. Support for future development of AI-based powertrain performance technology is offered by the identification of key training-data priorities, requirements, and considerations that underpin the performance of the data-management, modelling, control, and decision-making functions in AI-enhanced powertrains.

9.7.1. Final Thoughts and Future Directions

Advances in artificial intelligence (AI) play a crucial role in ongoing efforts to optimize the performance of vehicles' powertrains. Human scientists and engineers cannot easily anticipate the control strategies that will maximize performance across all demanding operating conditions or produce the best trade-offs among multiple conflicting goals, such as minimizing power loss whilst ensuring meeting stringent emissions regulations. AI techniques based on sensor fusion, predictive modelling or reinforcement learning are also enriching vehicles' safety and dependability by addressing hard problems in the realm of fault detection and isolation or unusual operation conditions.

Potential and ongoing control innovations presented in the literature are briefly summarized. The presented methods are research-oriented; they must undergo further development, validation, integration into a cyber-physical system, and evaluation during realistic driving conditions before being deployed into series-production vehicles. Practical deployment in series-production vehicles requires careful consideration of the entire lifecycle, including the dedicated test methodology for safety validation, the introduction of redundancy and fail-safe modes, and the identification of the installation's vulnerability to cyber attacks.

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