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Harnessing Artificial Intelligence for Enhanced Vehicle Control and Diagnostics

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Abstract

Automotive systems are becoming increasingly complex, with new technology being included to meet safety, performance, standardization, and cost targets. Control systems are an essential part of the increment just of such technologies. Artificial Intelligence (AI) has been proposed to play an important role in vehicle control, helping to create self-driving solutions and enhancing the overall vehicle stability and efficiency, particularly in extreme operating conditions. By adopting suitable supervisory control actions, AI can help recover vehicle operations when these are outside the range of standard control solutions and have the onset scenario of different failures. In addition to these benefits, designed AI tools, in particular Neural Networks, appeared to be adopted and developed for diagnostics purposes, where learning from collected 'experience observations data, often not possible to be generated with simulations or under controlled conditions, is required. This paper presents a review of designed AI tools applied to automotive vehicle control optimization, diagnostics, and fault detection purposes.

Keywords: Harnessing Artificial Intelligence, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM),Computer Science, Data Science,Vehicle, Vehicle Reliability

1. Introduction

The predictions made by futurists back in the 1980s have finally come true with connected and autonomous vehicle technology emerging on our roads. These technologies use a wide range of sensors including LIDAR, radar, ultrasonic, and cameras to build situational awareness about the environment and at any given point in time, make a decision on vehicle trajectory, environment, vehicle-to-vehicle, and vehicle-to-infrastructure communication technologies.

In addition to the sensors and the ability of autonomous vehicles to make a decision based on the information of the environment, it is extremely important to have network latency and vehicle latency that share the decision with the cloud or edge server. Indeed, with the continued development of faster supercomputing technology, the AI/ML approach requires significantly less hardware in comparison to the edge computing servers. Even with limited computational resources on an autonomous vehicle, stakeholders must ensure overall software robustness concerning handling environments falling outside the trained data. This is where transfer learning and reinforcement learning for decision-making play a key role in ensuring safe vehicle operation.While AI deals with vehicle autonomy algorithm decisions, hardware control is the next important step in ensuring vehicle safety. Specifically, AI has to be thoroughly integrated with hardware control, including the Long-Short Term Memory Networks (LSTM) to predict the next decision based on training real-time data. In non-autonomous vehicles too, AI holds a wide range of capabilities to get various functionalities done, with just a mobile-like device. Specifically, AI can be used to perform body control for predictive maintenance of the vehicle. This needs slimmer Learned Compression Machines (LCM) than regular hardware control. Specific LCM parts are IC layout design (less redundancy), electromagnetic interference control, path planning, tire-road handling issues, and predictive analytics algorithms. Yet, except for the emergency brake system, AI cannot claim to make decisions. AI/ML should be able to build what is referred to as "Cast Safe Capability" stringent vehicle performance, and to achieve this, robustness and safety architecture must be in place. Some of these are Patternological Watermarking Schemes, Direct Hidden Layer Length Control, and Probabilistic Robustness. In this way, AI-based control is only as good as the robustness guarantees that are in place.

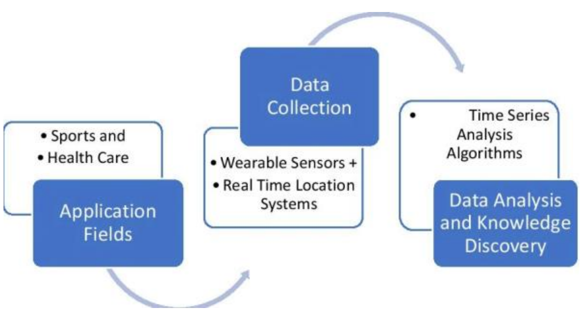

Fig 1: Application fields and Scope of the AIBSNF framework

1.1. Background and Significance

Modern vehicles are increasingly capable of providing sophisticated in-vehicle and remote services by enabling a host of vehicular and driver attributes, connecting them from inside and outside the vehicle to the external world, and eventually incorporating wider and more various services into a vehicle to support their occupants' safety, ubiquitous connectivity, and personalized traveling experiences. Over the years, the extent to which vehicle design has involved information and communication know-how has been evolving from low connectivity (mainly through the on-board embedded sensor system) to vehicle-to-vehicle communications (V2V), vehicle-to-infrastructure communications (V2I), vehicle-to-Internet connections, and vehicle-to-everything (V2X) communications. Together with the continuous promotion of in-vehicle infotainment and various driver assistance systems (DAS), sensor systems of the current vehicle has been more and more widely taking the form of in-vehicle sensor network platforms, and the degrees of information available in a vehicle's environment is being extended over a wider area through the vehicular cloud infrastructure.

To provide a truly personalized and efficient motorist experience, car information systems should combine innovative driver support for diverse applications such as driver assistance, vehicle-to-vehicle (V2V) communication for increasing the level of road safety, toll collection, and traffic management using vehicle-to-infrastructure (V2I) networks where vehicle actuators and sensors are utilized to cooperate with static roadside equipment, infotainment and value-added services, advanced diagnostics platform-based cloud services for vehicle prognostics and health management. The paradigm of the vehicle as an information system is an all-new point of view that in the last years has had enormous development, translated into the modern concept of Connected Vehicle. In recent years, the automobile market evolution has provided modern vehicles with increased electronic content to computerize primary control functions to improve energy management and optimize performance. Vehicle systems and components are controlled and managed through control area network (CAN) and local interconnection network (LIN) buses, truly minimizing wiring system and costs. In parallel, the diagnostic capability of onboard installed control units is always more robust, and car manufacturers can rely on this to develop innovative working strategies aiming to reduce warranty costs.

1.2. Research Aim and Objectives

It is first important to describe the purpose of the work. The overall goal of this thesis is to advance reliability and safety in the context of road vehicles. This will be achieved using artificial intelligence to predict the remaining useful life of mechanical and electronic components. Within the general research goal, several main objectives are pursued.

The first is to develop a solution to predict vehicle component failures using historical data. [9] For this, basic data analytics must be performed, including an extensive exploratory process, feature engineering, choosing a predictive model, and development of a performance measurement mechanism. More precisely, the research intends to use AI techniques and develop methodologies to predict the remaining useful life (RUL) of automotive batteries and turbochargers.

The second main objective is to generate an objective and standardized dataset upon which vehicles' computer systems' performance can be tested within a simulated road environment. The CODA research project will be used to achieve this aim. CODA is a benchmarking software package and the associated data sets that rigorously assess the degree of functionality of vehicles on European roads. This solution can be used to validate real-time failure detection and prediction AI algorithms on a large, dynamic, real-world dataset. [8] The third main aim is to develop a tool to monitor the performance of vehicles under a simulated road environment. The developed tool shall facilitate vehicle fleet monitoring towards the objective of reliability and safety enhancement. Finally, the last but least important objective is the design of a real-time failure detection and prediction model for the automotive components through data received using vehicle telematics, which are real-world data and can validate the predictive models.

This leads to a new generation of control strategies, which are best suited to continuous real-time adaptation and personalized learning. Research in this area has grown very rapidly to cover many aspects dealing with AI-inspired advanced modeling. It is suggested, however, that a new research emphasis should be placed on the actual vehicle autonomous functions control architecture itself. Hence, the pipeline of these AI functions into a control methodology is considered as a new and distinctive feature of the proposed research. This architecture is required to have variable resolution of intervention, as well as a self-diagnostic capability.
The developed technology becomes elegant in its intervention and hence will be essentially transparent to the driver and passengers. Aircraft intervene to prevent hazardous events, but without creating stress or doubts about skilled human control. Current automotive experimental vehicle infrastructures are large vehicles "Rube Goldberg's", cobbled together usually for a specific prototype application. They struggle to combine genuine human safety with actual, as opposed to nominal, research data returns. The proposed vehicle control system aims to integrate the decision-making processes and take from the driver the major burden of traffic control.

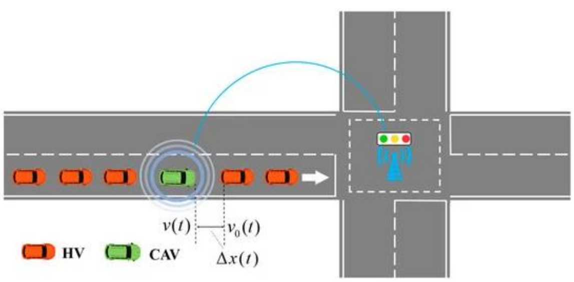

Fig 2 :Schematic diagram of the traffic scene at the intersection.

2. Artificial Intelligence in Vehicle Control

AI, specifically machine learning, is beginning to have a big impact on vehicle control. Vehicles with over-the-air updates and the Internet of Things are becoming cyber-physical systems. They are constantly changing their software. Typically, the impact of software changes on vehicle control is currently addressed by extensive testing. Tests fail for those unforeseen blending of inputs, such as failures of sensors or obstruction of sensors, that require control reprogramming. Those non-failure changes that require reprogramming also benefit from machine learning by using the data created by the many vehicle miles of everyday usage.

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The use of machine learning to acquire maps and assist vehicle control is now the most widespread application of AI to vehicle control. Mobileye and radar (LIDAR acting on their behalf) are the best-established developers of vehicle map infrastructure. Their product offers driving assistance features for ADAS and L3 operations. The data + AI business model includes being an established supplier for driver experience mapping for HD maps for automated vehicle operation. The consumer-to-creator business model may be faced with current perception limitations in developing an IPC (Integrated Pathway Control) application for unknown future sensors. Creating such unknown needs for a History of Mapping and Machine Learning able to use real-world evidence for validation of a new map that will generate data suitable for a new self-driving feature.

2.1. Machine Learning Algorithms in Vehicle Control

Automakers worldwide have come a long way in automotive technologies such as advanced driver assistance systems (ADAS), partial or fully automated driving systems, and augmented reality user interfaces. These breakthroughs have been made largely possible by the increasing application of sophisticated machine-learning algorithms in the automotive realm. Machine learning is an artificial intelligence application that uses statistical algorithms to enable computer systems to learn new tasks. The data-driven performance of machine learning algorithms in pattern recognition, perceptual cognition, and clustering has seen them steadily replace traditional signal processing, rule-based systems, and other conventional algorithms in the development of advanced vehicle control and diagnostics.

In conventional control algorithms, it is conventional for the vehicle's motion to be determined in parts based on the human driver's lead and in parts based on the vehicle and traffic regulations. This necessitates the intervention of the human driver at crucial moments such as overtaking, entering a highway, and negotiating including towns and construction sites. Although human drivers have an unrivaled cognitive ability to assess situations, detect, and respond to other road users, they are prone to making errors whenever they are overwhelmed and/or mentally and physically fatigued.

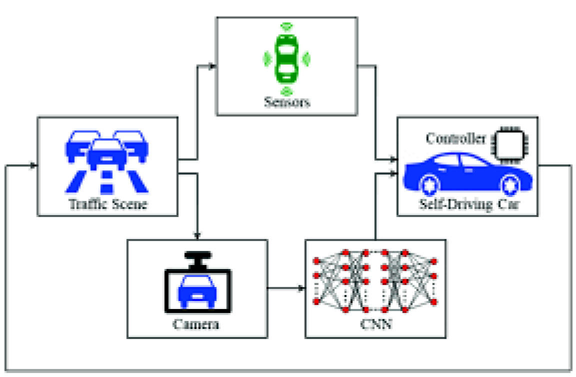

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Fig 3: Deep Learning and Control Algorithms of direct Perception for Autonomous Driving

2.2. Neural Networks for Adaptive Control Systems

The most straightforward approach to using AI for control is to program control rules into a computer as an expert system. Expert systems can express the specific and complex knowledge of human experts. They can solve specific problems such as controlling a specific process or machine. Expert systems can be based on if-then rules to a certain extent and can adapt to new situations. However, they do not acquire knowledge by learning from experience. The decisions of expert systems are based on the knowledge given, and the expertise of the expert system depends strictly on the knowledge and the rules in the system. Therefore, the knowledge and rules used in the expert system are very important. The quality of an expert system is mainly determined by the effectiveness of the knowledge processed. However, standard expert systems may require lengthy knowledge acquisition by experts. In the case of control systems for dynamic and complex plants such as fast automotive vehicles or robots, appropriated knowledge is hard to fully exploit by control expert systems. Neural networks exploit the learning capability and the parallel structure of the brain and have been used in the automotive industry for controlling a variety of subsystems such as transmissions, engines, steering, braking, and suspensions. In these applications, the ability of neural networks for adaptation and self-learning is exploited, and they are used to replace the transmission developed through system identification.

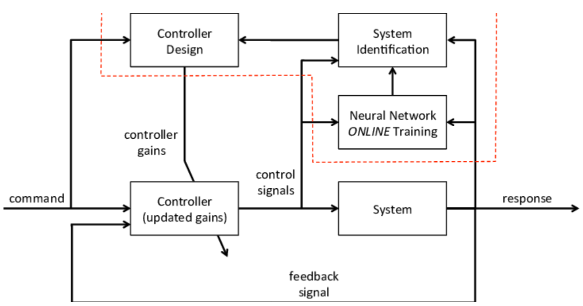

Fig 4: Indirect Adaptive Control Using a Neural Network With Online Training

3.Artificial Intelligence in Vehicle Diagnostics

Real-time condition diagnostics provide the operational feedback required by many of the advanced control and optimization techniques to improve vehicle performance or passenger amenities. The diagnostics can identify defective components or otherwise anomalous behavior of the vehicle. The advent of advanced diagnostics is the increased use of electronic control systems for various vehicle systems and components. Traditional diagnostic approaches address the requirement for monitoring complex electronic vehicle control systems, with the analysis of signals used in their operation. Tools incorporating state-of-the-art signal processing techniques are now the norm.

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The advent of more sophisticated artificial intelligence and machine learning approaches is seeing the incumbents augmented with these tools. Data-driven diagnostics are predicated on having vehicle signals available or being able to easily record them. Most diagnostics used in mass-produced vehicles in the current market are model-based methods. These methods are based on the comparison of measured signals, extracted from the numerous controlled stress tests to predetermined thresholds. Advanced diagnostics generally have no general noise rejection capability. The translational and rotational dominance observed during normal operation of the vehicle aids in the diagnosis of any subsystem malfunction.

It is the non-translational and non-rotational mechanical movements that are associated with any of the vehicle subsystems that reveal their operation. The ability to remove translational and rotational sensations through the use of hydraulically actuated and semi-active Actively Controlled Engine Mounts (ACMs) and Active Suspension Dampers (ASDs) hampers the feel of the vehicle operator. The haptic feel at the vehicle steering wheel of the mechanical nature of any subsystem fault is undesirable. The deliberate lessening of the feel of the operational systems has had an impact on the feel of the electric vehicle response. The application of advanced artificial intelligence and machine learning techniques provides avenues to restore the haptic feel experienced by the vehicle operator and an integrated interrogation of the electronic signals, available through the electric vehicle control system, using the keyword 'vehicle'.

3.1. Fault Detection and Diagnosis Using AI

The problem of fault diagnosis of vehicle faults has attracted considerable attention among researchers. One of the reasons for the increased interest in the field is that it has both economic and safety implications. In this context, machine learning-based models have shown some promise in the area of vehicle fault detection and diagnosis.

In a work by Pan and Tang, a fault diagnosis model based on the accumulated energy signature analysis method was developed. The AE method bears certain advantages such as wavelet-based signal analysis and feature extraction. The support vector machine was used as the learning algorithm and was implemented with success.

Kundu and Harb also developed a fault diagnosis model. Normal acceleration, jerk acceleration, harsh braking acceleration, and power cycling were obtained from a single-dimensional acceleration signal. These signals formed the inputs of an artificial neural network model trained with a backpropagation algorithm.

Robles et al. produced a system that could monitor the ever-changing behaviors of a train vehicle. A variety of variables were selected, including velocity, acceleration, environmental variables, maintenance records, and maintenance events, which were used to build the artificial neural network. Results showed that this technique can be successfully implemented and reduce track access costs.

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Further contributions in the optimization of preventive maintenance policy of railway infrastructures have been reviewed by Robles, et al. The cost of corrective maintenance was above average which led to the conclusion that optimization, based on the detection of a range of faults and their prognosis during the period indicated by this study, recognized a significant advantage in enhancing the management of installations. In this context, incorporating a damage prognosis insight into the existing system was expected to support the optimization of the rail maintenance policies, notably through cost reduction. However, the results from fault predictions depend to a large extent on the quality and quantity of available condition monitoring data. A recognized research gap is the limited availability of appropriate low-cost measurement techniques for multidimensional monitoring of the structure of a vehicle.

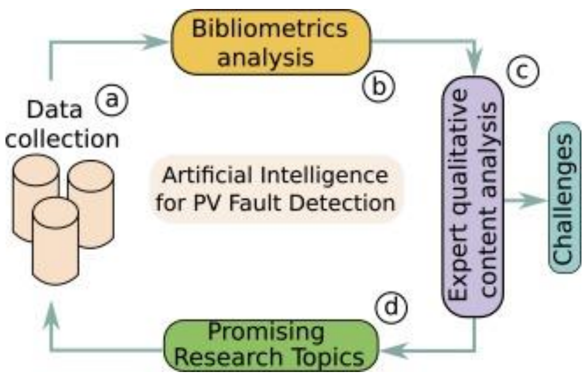

Fig 5: Fault Diagnosis of Photovoltaic Systems Using Artificial Intelligence

3.2. Predictive Maintenance with AI

To enable predictive maintenance for the automotive industry and increase the service life of vehicles, both safety and operational performance, while reducing costs, the development of AI-based tools that can forecast the occurrence of defects in key vehicle components is of utmost importance. By using machine learning techniques on vehicle data, not only can the key deficiencies in-vehicle components be detected, but they can also be forecasted. This chapter will introduce several AI tools focused on predictive maintenance for the automotive industry, including AutoPrognosis, Mastering Auto-Top-off, VMI, One-Tube, PdM, etc. Recently, AI-based tools have been successfully developed in the domain of automotive maintenance, aiming to improve the performance of predictive maintenance to increase operational availability and lower support costs.

In the automotive industry, the focus is mostly on residual useful life (RUL). The excitation of predictive alarms is not useful because the service cannot be rescheduled ad hoc in proximity to the alarm condition. The creation of proper warnings is not the only task assigned to the RCM

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approach, which also provides important information about the size of the opportunity windows. Larger opportunity windows are preferred, especially for components characterized by very long refurbishment procedures, for the maintenance activity.

4. Case Studies

4.1 Case Study 1: Maximizing SoC through Real-time Dynamic Management (Airdrive Intelligent Energy Management)

We now present a use case of dynamic charging for a real-world implementation, in the form of the Airdrive intelligent energy management system. Airdrive owes its principles to a fundamental property of lithium-ion batteries, which have highly non-linear and highly temperature, concentration, charge, and discharge-rate dependent power and energy charge-processing capabilities. Most lithium-ion batteries are operated at moderate ambient temperatures with no attempt to alter the internal temperature of the cell. This implies that the effective rate of charging or discharging is strongly affected by the thermal control of the cell being charged or discharged. A single cell can sustain or accept very high charge/discharge power levels, in a very wide SoC range, without showing significant indications of aging. Operating the cells at high SoC at high T can cause the highest aging if these conditions are sustained for prolonged periods with no attempt to optimize the charge acceptance and dissipation. Such rates can be achieved when special conditions are present. These unique charging properties imply the potential to use them in everyday life.

However, there are high-temperature ranges in which the cells must not be rapidly charged or discharged: the charging and discharging currents above the stopping point would produce the conditions that engineers directly involved in Airdrive technology observed in the test records of a few thousand cars over the last three years. A use case where short-term store fast refueling would be beneficial is electric car sharing: electric car sharing operators can benefit from storing the cars between charges at high SoC because the users expect a decent level of driving experience at the moment of car pickup. Stabilizing or leveling the SoC distribution in a car fleet throughout each day would also benefit grid operators, who would have predictive maximum peak demand disposal. Each single battery could store additional energy during the morning relatively low-demand time, and this additional energy could be used to buffer the maximum demand during regularly occurring higher-demand hours. The tiered fluctuating energy use peak power can also cause a less frequently occurring high demand, which would be predictable by looking at the maximum aggregate energy demand, as discussed in the following section. The net result would be a lower demand on the generating system during the higher demand hours and a better load leveling, reducing the generating and distribution system capacities wastage during less frequent, less predictable, but cumulatively expensive grid emergencies.

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4.1. Autonomous Vehicles The search for vehicle control autonomy has been underway for many decades. The recent advances in machine learning and the so-called reinforcement learning, have enabled the possibility of achieving such control for a plethora of public domain virtual driving simulation environments. Machine learning techniques have made much progress in specific driving situations. Control is not only probing local minima in virtual driving simulations but also encoding common sense, values, and ethical behavior through one way of training a neural network.These examples demonstrate the potential of AI and ML to address critical vehicle control challenges: high-level perception needs to arrive at an accurate representation of the scene, predicting the behavior of other actors and hence being able to plan around them, and most importantly learning an efficient way to cope and adapt to all of these given the very large number of input features and states that have to be used for decision-making.

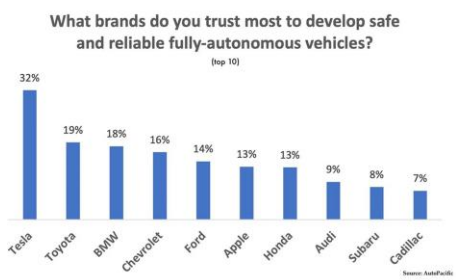

Fig 6: Study Says Tesla the Most Trusted Brand To develop Autonomous vehicles

5. Challenges and Future Directions

Vehicular safety is a key concern, especially due to the severity of motor vehicle accidents. Major advances in multiple technologies have been challenging, but to make highly intelligent vehicles possible and pervasive, there is no solution but to deepen research in AI. AI has become a single body of knowledge in computer science taking up the challenges of software, algorithms, and systems that can reason and act rationally and effectively like humans. This paper discusses our research in developing functioning AI demonstrators that can enhance the control of road vehicles, by autonomously ensuring safety and a good level of user satisfaction. It also conveys our conviction that the specific challenges of AI make it a fertile ground for research in other fields, particularly in computer science-related subjects.The need for considerably enhanced vehicle control capabilities has recently given renewed interest to AI. In this paper, we illustrate this by presenting two functional AI demonstrators that we have been building in recent research: SIRoNE4 and SIRoNE-DIAG. SIRoNE4 is an autonomous mobile robot that is built upon the software of SIRoNE, a three-wheeler electric vehicle that is being used in an extensive mobility study. SIRoNE-DIAG does not physically alter the real vehicle. It only uses its ECU to observe and alter data flows. Also, an important area of AI research consists of the efforts to explain and have agents report decisions. What operation did the agent implement? What simple variables were used to implement it? What is the model in the environment used by the agent to implement its operation? When do the values of simple variables trigger the operations the agent implements? In this sense, a theoretical framework has been proposed. Several existing cognitive architectures can also support the implementation of these functionalities.

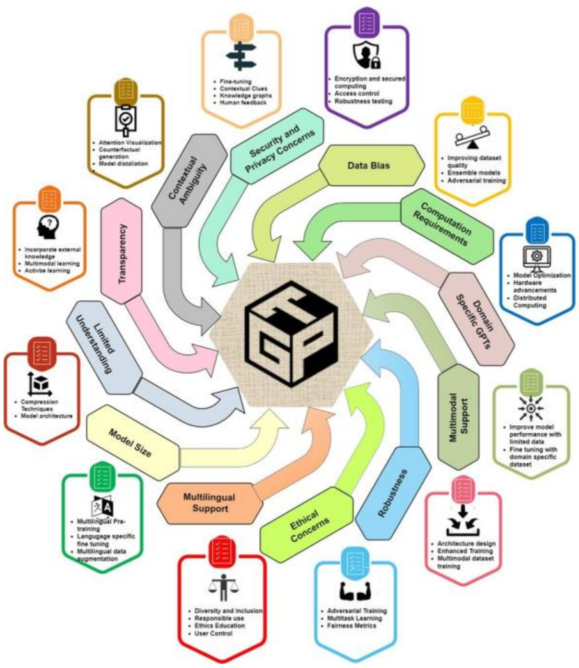

Fig 7: Challenges and Future Directions

5.1. Ethical Considerations in AI for Vehicles

Arguably, the most significant application of AI in vehicles is vehicle control. One can reasonably expect that AI can provide more sophisticated and safer vehicle control than is currently available through traditional microprocessors and digital signal processing technologies. Nevertheless, one is also mindful of the ethical issues created by such sophisticated use of AI. One might ask, "Do we trust ourselves not to perform aggressive driving?" AI technologies may naturally resort to actions (like maneuvering or other actions commonly associated with more aggressive driving) that are not malign in themselves but may be socially dangerous. Safe world models lead to safe level planning according to which the future states that consider the value-based safety function. The reactions of human drivers under stress are taken into account. We have developed a new operational design methodology, which ensures that the more complex machines are transparent to the human users. Concerning explicit traffic issues on motorways, we have developed smart cruise control or ACC (Adaptive Cruise Control) which safely deals with free space in front of the vehicle.

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From an ethical viewpoint, moral decisions made by AI in vehicle control touch upon a serious heavy challenge, which threatens the groundwork of AI itself. Ethical thinking has more than 2,000 years of experience in establishing the essence of values (like safe operations) within complexities. It has explored groundwork and backgrounds, which seem naïve to even the keenest contemporary AI researcher. Our approach is to supply the ground with ethically important values and to use these as a target and background when dealing by better understanding and assessing the complexities that had been identified earlier. AI constructs and applications take advantage of this human heritage. Our AI systems utilize the same background when they interact with humans and share the very same interdisciplinary ethically perceived activities. Nevertheless, to fully embrace the benefits of AI in the case of motorways, we need to reshape our car-based technologies and make them accessible once more. The AI knowledge model, comfort, automation, and collaboration provide a first insight into such a reshaped foundation. The understanding of perception coheres nicely with ethically informed AI vehicle control, and vice-versa. The onset of perception is the establishment and recognition of itself. At an early age, infants are capable of distinguishing cars from other members of the animal kingdom, such as cats and buses.

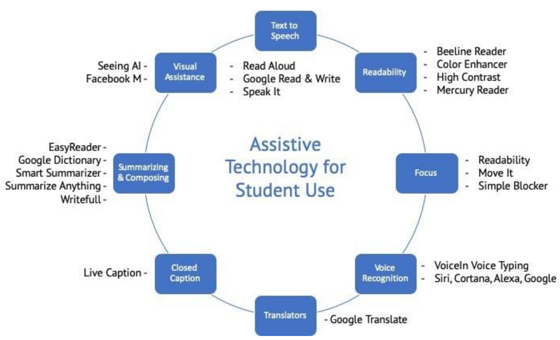

Fig 7 : Ethical Considerations When Using Artificial Intelligence

5.2. Potential Technological Advancements The incorporation of artificial intelligence (AI) into current technology leads to considerably enhanced vehicle operation and maintenance systems. Both the partials (PHEV) and full hybrid electric vehicles (FHEV) utilize data-driven techniques like fuzzy logic, neural networks, and genetic algorithms to control the complex power flows between both the engine and the electric motors, and the battery and the engine/emission control system. The use of hybrid technology significantly increases the performance of the control strategies selected, incorporating both closed and open-loop energy management strategies. This significantly advances vehicle fuel economy, and the use of direct marketing strategies and detailed mapping further advances this. The ever-increasing design complexity and the consequent increased powertrain system interaction have the potential to significantly improve through the use of these advanced control strategies. These control strategies and the support systems used also require the FHEV/PHEV control systems to robustly lend into safe modes/initiatives as required.

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The application of these somewhat classified technologies to vehicle control systems necessitates vast advances in system identification capabilities and the management of sensors and actuators. They must be constructed robustly to the point of ensuring that the vehicle can operate far from the nominal conditions without sub-system and vehicle damage occurring. This advanced use of AI-type algorithms significantly adds to the cost of these vehicles because of the relatively expensive calibration and the vehicle prototype testing that was required. Furthermore, BIW designs then had to be constructed to accommodate this additional needed complexity, and the battery compartment, the motor compartment enclosure, the engine/power management control systems, and the transmission design/cost could all substantially change. These types of vehicle control system-advanced management features must sensibly interconnect with the other vehicle safety programs, including ABS/ESC/traction control, and stability programs. The artificial intelligence advanced control strategies fit almost uniformly with the FMEA 3 supervisory controllers. Maintaining high fuel economy, system performance near the vehicle limits, and maintaining bilateral safety of smooth power flow asymmetric stresses organizational interaction, design complexity, and testing vehicles over a variety of driving regimes and vehicle terrains.

6. Conclusion

In conclusion, this paper highlights a unique application of AI that is yet to be addressed by researchers: an AI vehicle control and diagnostic system. We capitalized on the power of imitative learning to address vehicle control and diagnostic operations governed by human decision-making entities, commonly termed drive-by-wire systems. Although we applied the model on wind systems, it is not optimally tuned to our best knowledge, and we call on efforts through the AI community to come up with a widely applicable DNN-RNN model for vehicle control and diagnostic operations. Such models can be used to address both autonomous and non-autonomous vehicles.

In the same way that pre-assembly operations are essential for the proper operational performance of the gear system in wind power systems, drivetrain, and gearbox issues are essential for energy optimization in vehicles. Advanced monitoring and assembly of vehicles can provide efficient human filtering and time-stamped annotated data of vehicles driven by humans. In this article, we described the possibility of using this data to develop both drivetrain vibration detection and gear assembly. To the best of our knowledge, both aspects have not been reported as an AI solution and might be of interest to an extended audience, especially for the vehicle community, since it forms a general control and diagnostic framework for vehicle applications.

6.1 Future Trends

Several future trends can be identified that will contribute to progress in developing the PID controller and diagnostics. Firstly, in the real-time on-board computers, the gradual migration from 16-bit microprocessors to 32-bit ones is expected soon. The computational capability of 32-bit CPUs will provide an edge for more intensive and large-scale applications that artificial neural networks (ANNs) and fuzzy logic (FL) support. Advanced embedded computing, through the significant expansion of memory size (from Kbytes to Mbytes) and the increasing quantity (2 and more) and speed (+1/2-1/3) of parallel microprocessors in embedded modules is expected. To a significant extent, all of these developments can be expected to fulfill the NANIDIE objectives dictated by the forthcoming changes in legislation and vehicle and electronics architecture.

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