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REVIEW

Multi-Sensor Fusion Techniques for Monitoring Emissions and Health of New Energy Vehicle Powertrains

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ABSTRACT

The rapid development of new energy vehicles (NEVs) has intensified the demand for accurate and reliable monitoring of both emission-related performance and powertrain health. In contrast to traditional vehicles, NEV powertrains are characterized by a high degree of interconnection between electrical, thermal, mechanical, and chemical subsystems that results in complicated dynamic behavior and degradation behavior. The conventional single-sensor or isolated-model monitoring systems are becoming less effective in dealing with the challenges during real-world driving conditions. Multi-sensor fusion in this regard has become one of the key enabling technologies to achieve higher levels of observability, robustness, and diagnostic capability in NEV powertrain monitoring. The paper gives an in-depth review of multi-sensor fusion that is being used to monitor emissions and powertrain conditions in NEVs. The review initially examines the monitoring requirements that are linked to various NEV architectures and sensing technologies, and the heterogeneous and uncertain character of multi-sensor data. Significant sensor fusion strategies, such as model, data, and hybrid strategies, are also presented systematically about their theoretical basis, implementation architecture, and trade-offs. The applications in emission monitoring and health management in powertrains are then considered, including real-time estimation of emission-related factors, fault detection, state estimation, and prognostics. Other critical issues in terms of data quality, computational requirements, strength, and explicability are also underscored. The synthesis of existing research advances and the uncovering of gaps are what make this review give a single view on the importance of multi-sensor fusion to develop intelligent, reliable, and sustainable NEV powertrain monitoring systems.

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1. Introduction

The swift transformation on the global platform to low-carbon powers has bolstered the creation and introduction of new energy vehicles such as battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEVs)[1,2]. With an ever-stiffening environmental legislation, mitigation of climate change objectives, and electrification technologies, NEVs are broadly viewed as a major door to sustainable mobility[3]. Relative to the traditional internal combustion engine-based vehicles, NEVs have enormous potential to minimize greenhouse gas emissions and enhance energy efficiency. Nonetheless, the environmental and functional advantages of NEVs highly rely on the real-time performance, stability, and well-being of their powertrain systems across the vehicle lifecycle.

The emission nature of NEVs is not as simple as it may seem because they are usually viewed as vehicles that do not produce emissions at the point of use. Their environmental footprint may be highly influenced by indirect emissions related to inefficiency in energy conversion, hybrid operation modes, hydrogen leakage, and component degradation. Simultaneously, the NEVs' powertrains, including, but not limited to: batteries, electric motors, power electronics, fuel cells, and auxiliary thermal management systems, work under highly dynamic and tightly coupled conditions. These systems can be aged, thermally stressed, electrically imbalanced, and subject to wear and tear that may result in poor performance, loss of efficiency, and loss of safety. As a result, proper tracking of indicators related to emissions, as well as powertrain well-being, has become an essential need to reach sustainable, reliable, and safe NEV usage[4].

Conventional methods of powertrain monitoring have also been mostly based on single sensor measurements or a single diagnostic model[5]. Although these techniques are fairly easy to apply, they are becoming too poor to deal with modern NEV systems. Single-sensor methods are often limited to observability and prone to noise and sensor faults, and will not observe multi-physical interactions of electrified powertrains. As an example, the degradation of a battery is not only affected by the electrical load profiles, but also by thermal gradients, mechanical stress, and environmental conditions. Likewise, the indicators that are related to emissions, including energy efficiency losses or unusual fuel-cell byproducts, cannot be accurately predicted based on a single source of measurements. These constraints spur the implementation of more sophisticated surveillance plans that have the capability to combine heterogeneous data from various sensors and data sources.

Multi-sensor fusion has become a potent paradigm applicable to solving the complexity and uncertainty of NEV powertrain monitoring[6]. Multi-sensor fusion methods can be used to improve state estimation accuracy, fault detectability, and noise resistance, missing data, and sensor failures by fusing complementary information in many sensors, like electrical, thermal, mechanical, chemical, and environmental sensors. Instead of using a single measurement or model, sensor fusion takes advantage of redundancy and diversity to form a more detailed and trustworthy system behavior representation. This power is especially useful with NEVs, whereby the multi-physics coupling and non-linear dynamics are inherent aspects of the powertrain.

In the last ten years, there has been a lot of research in sensor fusion techniques in the automobile industry. Kalman filtering and observer-based methods have been extensively used as model-based methods to perform state estimation tasks such as battery state-of-charge (SOC) estimation and state-of-health (SOH) estimation[7]. Data-driven and artificial intelligence (AI)-based solutions have become of higher interest in recent times, as more and more high-frequency onboard data are becoming available, and due to the increase in computational power. Machine learning and deep learning techniques have shown a high potential in the extraction of complex patterns in multimodal sensor data and the possibility of adaptive and real-time monitoring in varying operating conditions[8,9]. Simultaneously, it has been suggested that to trade the interpretability of physics-based models, generalization ability, and computational efficiency, hybrid methods incorporating both physics-based modeling and data-driven learning methods have been suggested.

The research on the use of multi-sensor fusion to simultaneously operate in emission monitoring and powertrain health management of NEVs is a challenging and dynamic topic despite these advances. The current literature tends to investigate single elements (i.e., batteries or motors) or work with emissions-related indicators or health diagnostics separately [10]. This review addresses this gap by proposing a unified framework that links emission-related indicators with component-level health monitoring, emphasizing the shared reliance on multi-sensor fusion and multi-physical data integration across NEV architectures.

Besides this, regulatory and industrial demands are in a state of constant change. On-board diagnostics, emission compliance, and predictive maintenance are starting to be turned into vehicle control architecture and fleet management systems. This trend makes more demands on monitoring algorithms in terms of robustness, explainability, and cybersecurity. The purpose of multi-sensor fusion methods, however, should not be limited to the high accuracy of the estimation but should also ensure the fault-tolerance, transparent decision-making, and scalability to real-life NEV applications [6,11].

It is in this backdrop that there is a need to have a thorough survey of multi-sensor fusion methods in the monitoring of emissions and health of NEV powertrains [3]. The review in such a way would be able to give a systematic perspective of the existing state of art, methodological trends, and research gaps that have to be filled to allow next-generation intelligent monitoring systems. The proposed review fills the gap between theory and practice in developing NEV systems by combining the knowledge base of sensing technologies, fusion methodology, and application areas.

There are three primary goals and the contributions of this review. First, it offers a combined view of the NEV powertrain monitoring needs on the basis of both emission and health considerations, with a focus on the multi-physical and data-driven issues that drive sensor fusion. Second, it theorizes, tabulates, and examines the available multi-sensor fusion approaches, such as model-based, data-driven, and hybrid, and their suitability, strengths, and weaknesses in the case of NEVs. Third, it surveys typical uses of sensor fusion in emission monitoring and powertrain health management and talks about future research areas, including digital twins, explainable AI, and edge intelligence.

The rest of this article is structured in the following way. Section 2 provides an overview of the monitoring requirements as well as the challenges regarding various NEV powertrain architectures. Section 3 is a review of sensing technologies and multisensory data. Section 4 gives and contrasts significant multi-sensor fusion methodologies. In Sections 5 and 6, it is described how it applies to emission monitoring and powertrain health monitoring, respectively. Lastly, Section 7 is the conclusion of the paper that presents the future research perspectives.

2. NEV Powertrain Monitoring Requirements

The electrified systems, multi-physical nature, and highly demanding environmental and reliability goals of new energy vehicle (NEV) powertrains determine the nature of their monitoring requirements [12]. As opposed to traditional internal combustion engine machinery, NEVs are significantly reliant on electrochemical, electromagnetic, and power electronic subsystems, whose behaviors of performance and degradation are closely intertwined. This means that proper monitoring should deal with the performance parameters in emissions and the health conditions of the critical parts of the powertrain working in highly dynamic conditions.

2.1. NEV Powertrain Architectures and Operational Characteristics

NEV powertrains include a wide variety of different architectures, such as battery electric vehicle, hybrid electric vehicle, plug-in hybrid electric vehicle, and fuel cell electric vehicle. Even though these configurations vary in energy sources and propulsion approaches, they have certain similarities in that they use electric traction motors, high-voltage energy storage, power electronic converters, and advanced control systems. The combination of various energy pathways and working modes results in a large level of complexity in the behavior of the powertrain, especially in transient driving conditions [13,14].

The key factors that control the performance of the powertrains in battery electric vehicles are mainly battery dynamics, inverter efficiency, and motor operation. The presence of hybrid and plug-in hybrid vehicles also makes them harder to monitor since they often alternate between electric and combustion propulsion, meaning that they experience loads and thermal conditions that change quickly. Electric vehicles powered by fuel cells bring about other difficulties in the cycle of electrochemical reactions, the dynamics of gas supply, and the control of water and heat. Such architectural variations compel that flexible monitoring structures are required that can come up to different system configurations and regimes of operation[15]. **Figure 1** illustrates the major NEV powertrain configurations and highlights key components relevant to emission and health monitoring.

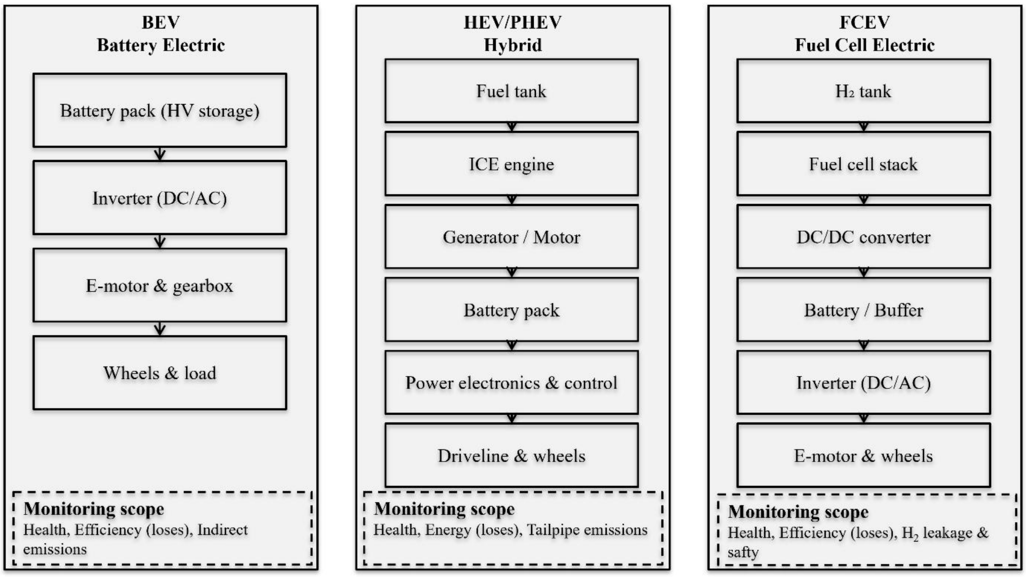

Figure 1. Schematic illustration of typical new energy vehicle powertrain architectures and associated emission and health monitoring scopes, including battery electric, hybrid electric, and fuel cell electric configurations.

2.2. Emission-Related Monitoring Requirements in NEVs

Even though NEVs considerably decrease tailpipe emissions, the monitoring of emissions is one of the necessary conditions because of the existence of non-exhaust emission sources and indirect emissions[16]. Inefficiencies in energy conversion in batteries, motors, and power electronics also add to energy consumption and subsequently to lifecycle greenhouse gas emissions. In hybrid engines, the activity of the combustion engine creates controlled emissions, which have to be observed in various circumstances during driving. In the case of fuel cell systems, the leakage of hydrogen and byproducts that are caused by degradation may affect efficiency and environmental impact.

Correct monitoring of the emissions in the NEVs thus goes beyond the traditional exhaust gas monitoring and demands estimation of the energy efficiency, power losses, and performance degradation due to degradation[17]. Such quantities are sometimes immeasurable directly and would have to be determined using some sensor signals scattered throughout the powertrain. The high reliance of emission-related indicators on both operating conditions, environmental, and component aging complicates the need to have reliable monitoring, especially in real-time onboard use.

2.3. Health Monitoring Requirements of Electrified Powertrain Components

Batteries, electric motors, power electronic devices, and thermal management systems are some of the key components of the NEV powertrains whose health is critically defined[17,18]. Direct effects on driving range, safety, and energy efficiency are battery degradation, such as loss of capacity, an increase in internal resistance, and thermal instability. There are also electrical stresses, thermal cycling, and mechanical vibration on the electric motors and inverters, which can result in insulation failure, bearing failures, and semiconductor malfunction.

The purpose of health monitoring is to identify faults early, monitor the degradation process, and assist in predictive maintenance [19]. To reach these goals, the constant estimation of the internal conditions and degradation indicators cannot be observed directly. Moreover, the interactions between electrical, thermal, and mechanical fields affect component health status and, therefore, independent monitoring methods are inadequate. Wholesome health assessment, thus, requires the incorporation of heterogeneous sensor data in order to obtain the complete range of degradation processes.

2.4. Challenges in Powertrain Monitoring under Real-World Conditions

Operating environments encountered in real life make NEV powertrain monitoring even more complicated due to the variability and uncertainty of the real-life environment [20]. The dynamics of the system are highly variable due to driving behavior, ambient temperature, road conditions, and charging patterns. Noise, bias, drift, and failures are common sensor measurements, and they might compromise the accuracy and reliability of monitoring. Also, the onboard computational capabilities are small, which puts a constraint on the complexity of algorithms and real-time performance.

The other vital challenge is to reach scalable and transferable monitoring solutions to multiple vehicle platforms and being used in different circumstances. Feedback control algorithms that have been trained on a particular powertrain setup or operation condition cannot be readily applied to other systems without intensive resetting. These issues point to the necessity of strong and flexible monitoring structures capable of addressing the uncertainty, heterogeneity, and complexity of the system [21].

2.5. Motivation for Multi-Sensor Fusion in Monitoring Requirements

The above monitoring needs highlight the shortcomings of NEV powertrains with single sensors and single models. The indicators and the health states associated with emissions are multidimensional in nature, with the interactions between various subsystems. Multi-sensor fusion offers a methodical method of incorporating supplementary data from different sensors in order to improve observability, upgrade the accuracy of estimation, and become robust to noise and sensor faults [22].

Through redundancy and diversity of sensor measurements, the fusion-based monitoring methods may be more accommodating to system nonlinearity, operational variability, and effects of system degradation. This feature is especially significant to NEVs, when precise and sound monitoring is necessary to meet emission reduction goals, achieve safety, and facilitate intelligent energy and maintenance of the systems. As a result, the multi-sensor fusion has now become a design specification of enhanced monitoring strategies in the contemporary NEV powertrains [6,11].

3. Sensing Technologies and Data Characteristics

Emission and health control in new energy vehicle powertrains depend on the sensing technologies, such as their availability and quality, that can measure the multi-physical conditions of complicated electrified systems [12]. The current NEVs are fitted with a broad range of sensors spread within electrical, thermal, mechanical, and even chemical subsystems. The products of these sensors are heterogeneous streams of data, which indicate various elements of powertrain operation and deterioration. The design and establishment of effective multi-sensor fusion structures require the understanding of the nature of these sensing technologies, their characteristics, and their limits, and the nature of the data they generate.

3.1. Electrical Sensing Technologies

The NEV powertrain monitoring is based on electrical sensors since electrical variables can give a direct indication of energy flow and efficiency of its conversion [23]. Sensors, voltage, and current are used at the cell, module, and pack scales in battery systems and in power electronic converters and motor drives. They are essential measurements that are used to estimate important states like the state of charge, power losses, and the level of electrical stress.

Besides fundamental voltage and current measures, more sophisticated measures of electrical sensing have been investigated to measure internal electrochemical and material properties, including impedance and frequency-response measures [24]. Such signals are especially useful to measure the battery health and degradation, although they tend to be susceptible to operating conditions and measurement noise. Electrical data has high sampling rates and a wide range of dynamic data, which makes it difficult to process and integrate with other sensing modalities in real-time.

3.2. Thermal Sensing and Temperature Distribution Monitoring

In the NEV powertrains, there is a significant role of thermal behavior in terms of emission-related efficiency and component health [25]. Temperature sensors are typically placed in battery packs, power electronic modules, electric motors, and cooling systems so as to monitor a thermal state and prevent overheating. Local temperature data are useful for thermal control and safety measures, and are typically not able to resolve spatial temperature gradients and localized hotspots.

In order to overcome these shortfalls, it has explored distributed temperature sensing and thermal imaging methods, which provide better spatial resolution but come at the sacrifice of a more difficult-to-use system [26]. Thermal variables are highly interlinked with electrical and mechanical variables, and when interpreting thermal variables, special attention to heat generation, heat dissipation, and environmental effects is to be made. Alignment and fusion of data is also a problem because of the relatively slow nature of thermal processes compared to electrical signals.

3.3. Mechanical and Physical Sensing

Physical and mechanical sensors offer information on the structural and dynamic status of powertrain components of NEV [27]. Vibration and acoustic sensors are extensively applied to the control of electric motors, bearings, and gearboxes, which allows detecting mechanical defects and abnormal working conditions. Rotational speed sensors and torque sensors provide direct measurements of mechanical performance and efficiency, and give the connection between electrical input and vehicle-level performance.

These sensors are especially useful to diagnose the faults and evaluate the degradation; however, their signals are frequently disturbed by outer perturbation and working fluctuations. Mechanical data are usually non-stationary and need complex signal processing methods to obtain significant features. Mechanical measurements, combined with electrical and thermal measurements, are thus required to obtain a complete health evaluation [28].

3.4. Chemical and Environmental Sensing

Chemical and environmental sensors are increasingly important in the reduction of emissions of NEVs and safety assurance, particularly on hybrid and fuel cell-based systems [6,27]. Hydrogen leakage in fuel cell cars and exhaust-related species in hybrid power-trains can be detected by gas sensors. Humidity and pressure sensors generate very important data on fuel cell functioning, battery efficiency, and the effectiveness of thermal management.

The ambient temperature and humidity of the environment play an important role in the behavior of powertrains and rates of degradation [29,30]. Nevertheless, data from chemical and environmental sensors are usually slower and less precise than electrical measurements. Their successful application, consequently, relies on the incorporation of quicker and more accurate sensing modalities by fusion methods.

The diversity of sensing technologies and their heterogeneous data characteristics are summarized in **Figure 2**.

3.5. Characteristics of Multi-Sensor Data in NEVs

The different sensing technologies used in NEV powertrains produce data with a very heterogeneous nature [6,31]. The sampling rates, resolution, accuracy, and noise level of measurements vary depending on the underlying physical processes they are measuring. Electrical signals are often extremely dynamic and high-frequency in nature, whereas thermal and chemical signals are much slower and are affected by the cumulative responses.

Besides heterogeneity, multi-sensor data are usually incomplete due to communication delays, sensor faults, or loss of data. Fixed correlations between sensor signals are not reliable because the operating conditions can change their values. It makes such characteristics difficult to directly interpret data and requires sophisticated preprocessing, synchronization, and normalization before fusion.

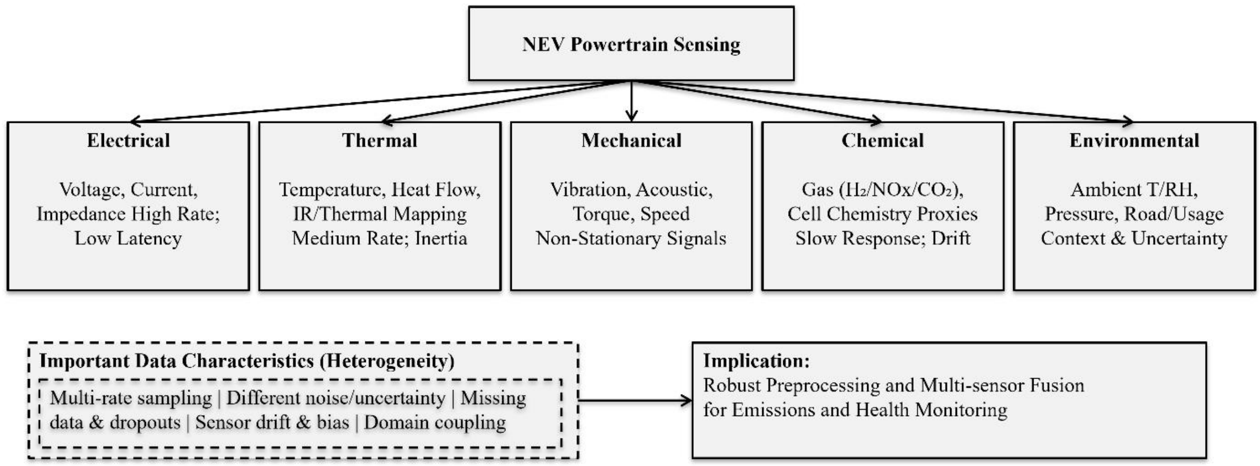

Figure 2. Taxonomy of sensing technologies deployed in NEV powertrains and the corresponding data characteristics across electrical, thermal, mechanical, chemical, and environmental domains.

3.6. Data Quality, Uncertainty, and Preprocessing Considerations

The quality of the data is one of the vital criteria that affect the performance of sensor fusion-based monitoring systems[32]. The estimation accuracy of noise, bias, drift, and calibration errors can be rated poorly unless it is tackled. Filtering, outlier detection, missing data, etc., are preprocessing steps and thus an integral part of any fusion framework.

Uncertainty quantification is also being increasingly accepted as a critical requirement, especially in safety-critical applications[33]. The proper depiction of the measurement uncertainty facilitates the fusion and decision-making process that is more robust and can be made when the sensor is in a degraded state or failure mode. The given considerations will further encourage the adoption of probabilistic and adaptive fusion methods that will be able to adapt to imperfect and changing data.

3.7. Implications for Multi-Sensor Fusion Design

The above sensing technologies and data characteristics entail an immediate implication on the design of multi-sensor fusion methodologies on NEV powertrain monitoring. Fusion algorithms should be able to serve multi-rate and multi-modal data at a reasonable computation cost appropriate for onboard. They should also withstand uncertainty, sensor failures, and operating conditions.

Multi-sensor fusion allows achieving a high level of observability of related indicators of the emission state and component health conditions that cannot be confidently estimated with the help of single measures[34]. Further evolution of the NEV sensing systems will keep scalable and adaptive fusion structures as a key challenge and opportunity in the research of powertrain monitoring. **Table 1** summarizes the major NEV powertrain components, associated sensing technologies, and primary monitoring objectives.

Table 1. Overview of NEV powertrain components, representative sensors, physical domains, and corresponding monitoring objectives.

Powertrain Component	Typical Sensors	Physical Domains	Monitoring Objectives
Battery system	Voltage, current, temperature, impedance	Electrical, thermal, electrochemical	SOC/SOH estimation, degradation tracking, safety monitoring
Electric motor	Current, speed, vibration, temperature	Electrical, mechanical, thermal	Fault diagnosis, efficiency assessment, and health monitoring
Power electronics	Voltage, current, junction temperature	Electrical, thermal	Loss estimation, thermal stress monitoring, and reliability analysis
Fuel cell system	Pressure, temperature, gas concentration	Chemical, thermal, electrical	Efficiency evaluation, leakage detection, degradation monitoring
Thermal management	Temperature, flow rate, pressure	Thermal, fluid	Heat dissipation assessment, system optimization

4. Multi-Sensor Fusion Methodologies

Multi-sensor fusion techniques have given the analytical basis of heterogeneous sensing information integration in novel energy vehicle powertrain monitoring [6]. Sensor fusion does not merely aim at pooling various data sources, but also at leveraging the complementary properties of these sources with the view to enhancing the precision of state estimates, fault detectability, and uncertainty-robustness. Since NEV powertrains exhibit multi-physical behavior, the fusion methodologies have to be able to deal with nonlinear dynamism, time-varying operating conditions, and varying data modalities. The section provides a review of the major types of multi-sensor fusion methods and the way they can be applied to emission and health monitoring.

4.1. Levels of Multi-Sensor Fusion

The various sensors can be broadly categorized according to the point at which multi-sensor fusion is used. Raw sensor measurements are fused at the data level, creating a single non-separable system behavior representation. This method allows retaining the most information, but it should have accurate time alignment and control over noise and uncertainty. Data-level fusion can be computationally intensive and vulnerable to measurement errors, especially when combining signals of dissimilar rates and noise properties [35].

In feature-level fusion, data denoting informative features is extracted and then consolidated on a sensor signal by first processing sensor signals and then combining their informative features [36]. Such a degree of fusion decreases the dimensionality of the data and may be more robust because it focuses on characteristics that are physically or statistically significant. The feature-level fusion is most popular in the field of fault diagnosis and health monitoring schemes, where features like frequency-domain measures or statistical measures describe the pattern of degradation.

Decision-level fusion is the combination of the results given by several independent models or classifiers, which process different streams of sensor data [37]. This design is highly modular and fault-tolerant because the underperforming decision units can be independently designed and modified. Nonetheless, decision-level fusion can trade off detailed information at more detailed fusion levels and is not usually as applicable to continuous state estimation.

4.2. Fusion Architectures and Implementation Structures

Sensor fusion architecture defines the flow of information, as well as the distribution of computational resources [38]. In centralized fusion architectures, all sensor data is gathered at one processing unit upon which a single fusion algorithm is implemented. This design enables global optimization and uniformity, yet can be characterized by excessive communication and computational overhead, especially when large systems are involved.

The distributed fusion architectures divide processing work among multiple local nodes, which perform a partial fusion or estimation using a subset of sensors [11]. The findings are then aggregated at a greater level to create an international forecast. Distributed architectures enhance fault tolerance and scalability, that needs to be with appropriate coordination and communication plans to provide uniformity. Hybrid architectures seek to combine the benefits of the centralized and distributed solutions by integrating local processing with centralized coordination, and therefore, they are of particular interest to complex NEV powertrain systems. **Figure 3** provides a unified framework for understanding the multi-sensor fusion structures discussed in this section. The characteristics and application scenarios of different fusion strategies are summarized in **Table 2**.

4.3. Model-Based Fusion Approaches

The sensor fusion approaches that are model-based are based on mathematical models of the behavior of the underlying physical process of the powertrain [39]. System dynamics are often modeled in state-space, and measurements of sensors as observations are included. Kalman filtering and nonlinear forms of Kalman filtering have been widely used to combine electrical and thermal signals in battery and motor condition estimation. These approaches provide a principled probabilistic approach to dealing with noise and uncertainty on the assumption that the model assumptions are reasonable.

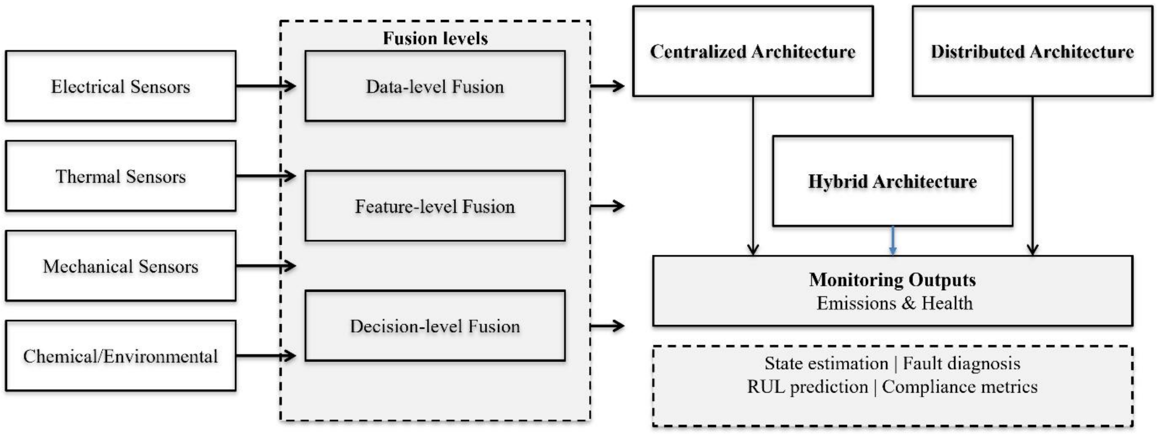

Figure 3. Conceptual framework of multi-sensor fusion levels and implementation architectures, illustrating data-level, feature-level, and decision-level fusion under centralized, distributed, and hybrid structures.

Table 2. Classification of multi-sensor fusion levels and architectures, including their characteristics, advantages, and typical applications.

Fusion Category	Description	Advantages	Limitations	Typical Applications
Data-level fusion	Direct fusion of raw sensor data	Maximum information retention	High sensitivity to noise, synchronization required	State estimation, real-time monitoring
Feature-level fusion	Fusion of extracted features	Reduced dimensionality, robustness	Feature selection dependency	Fault diagnosis, degradation analysis
Decision-level fusion	Fusion of independent decisions	High modularity, fault tolerance	Information loss	Classification, alarm systems
Centralized architecture	All data processed at one node	Global consistency	High computational load	Battery monitoring
Distributed architecture	Local fusion with global coordination	Scalability, robustness	Communication complexity	Fleet-level monitoring

The fusion-based monitoring has also been developed with observer-based methods, like sliding mode observers and adaptive observers [40,41]. Such procedures are strong in terms of modeling uncertainties and disturbances, and therefore are appropriate in fault detection and isolation. Digital models based on physics also allow interpreting the interrelation of multi-domain knowledge, such as electrical, thermal, and mechanical conditions. Nonetheless, model-based fusion techniques tend to need good parameterization and might fail to capture complicated degradation effects without regular recalibration.

4.4. Data-Driven and Learning-Based Fusion Methods

Fusion techniques are becoming more and more popular with the rise of onboard sensing and data storage in NEVs, which is based on data [42]. Machine learning algorithms have the capability to acquire a rich relationship between multi-sensor data without physically modelling the relationships, and this allows adaptive monitoring when operating under a variety of conditions. Classical learning-based fusion, e.g., support vectors and ensembles, has been used in fault diagnosis and classification with regard to emissions.

More recently, deep learning architecture has been proposed to combine multi-modal sensor data end-to-end. Convolutional neural networks are useful in the extraction of spatial and spectral features, whereas the recurrent and attention-based networks are useful in capturing the temporal dependencies of sequential data. They have been shown to perform well on nonlinearities and high-dimensional data, but frequently require a large labeled set, and cannot be easily understood, so their use raises safety-critical applications in the automotive industry [43].

4.5. Hybrid Fusion Strategies Combining Models and Data

In order to overcome the weaknesses of fully model-driven or fully data-driven methods, hybrid fusion methods have been suggested. These techniques combine physical models with learning-based elements, which allows the inclusion of domain knowledge but are flexible. PIL models take advantage of model constraints to do data-driven training to enhance generalization and data requirements.

The hybrid fusion approach is especially as a potential on NEV powertrain-observing, where physical understanding about energy conversion and degradation processes can be used alongside data-driven pattern recognition [44]. Hybrid solutions can provide a way out by being interpretable and flexible enough to implement in a robust and explainable monitoring solution that is acceptable to industries.

4.6. Computational and Practical Considerations

Onboard computation power, bandwidth, and real-time considerations limit the practical application of the multi-sensor fusion techniques with NEVs [45]. Fusion algorithms should be reliable when they run with limited processing power and memory, and be responsive enough to be useful to safety and control applications. The complexity, scalability, and resilience to sensor faults of an algorithm are thus important factors in the choice of method.

Also, the fusion algorithms that will be integrated with vehicle control and diagnostic systems must be compatible with existing hardware and software architectures. These utilitarian implications have an effect on the trade-offs between accuracy in fusions, computational efficiency, and complexity of the system.

4.7. Methodological Implications for Emission and Health Monitoring

NEV powertrains directly depend on the effectiveness of emission and health monitoring, which depends on the type of fusion methodology used [46]. Continuous estimation of states and control over compliance with regulations are better addressed using model-based methods, while the complex degradation patterns and operational variability are better addressed with the help of data-driven methods. Hybrid strategies provide an appealing trade-off, as they provide precision, strength, and readability with regard to monitoring in a variety of applications.

In general, the methodologies of multi-sensor fusion are the main analysis tools that can be utilized to achieve the improved monitoring of emissions and health of the powertrain in NEVs [6]. They need further elaboration and growth to satisfy the growing need for sustainability, reliability, and smart car performance. **Table 3** compares representative multi-sensor fusion methods in terms of data type, advantages, and limitations.

Table 3. Representative model-based, data-driven, and hybrid multi-sensor fusion methods applied to NEV powertrain monitoring.

Fusion Method	Category	Data Type	Key Advantages	Main Limitations
Kalman filter variants	Model-based	Electrical, thermal	Probabilistic framework, real-time capability	Model dependency
Observer-based methods	Model-based	Multi-domain	Robust to disturbances	Parameter tuning complexity
Machine learning fusion	Data-driven	Multi-modal	Strong pattern recognition	Data dependency
Deep learning fusion	Data-driven	High-dimensional	Nonlinear modeling capability	Interpretability issues
Physics-informed learning	Hybrid	Multi-domain	Balance of accuracy and interpretability	Implementation complexity

5. Applications in Emission Monitoring

New energy vehicle powertrains' emission monitoring is not just limited to the conventional exhaust monitoring; it involves a multifactorial evaluation of energy conversion efficiency, operating condition, and degradation of the components [17]. The multi-sensor fusion has become important in ensuring proper and sound monitoring of the emission in the context that incorporates heterogeneous data from electrical, thermal, mechanical, and environmental sensors. In this section, the primary application scenarios where sensor fusion methods have been used to assist in the emission measurement during NEV systems are reviewed.

5.1. Real-Time Estimation of Emission-Related Indicators

A lot of the emission indicators used in NEVs cannot be directly measured, and one has to deduce the indicators using observable system variables [47]. Multi-sensor fusion has also been extensively used to estimate real-time amounts of energy consumption, power losses, and efficiency degradation.

With a combination of electrical data collected by batteries and power electronics, thermal data, and mechanical sensor data, fusion-based methods can be used to embrace the complex interactions that govern energy conversion processes.

In the case of hybrid and fuel cell cars, the estimation of emissions can often be combined with signals related to various energy sources, as well as working modes [15,48]. The sensor fusion allows a steady-state measurement of emission-related states in the diversity between electric and combustion-based operation and enhances the precision of the estimation in transient situations. Such features are especially significant in the case of onboard applications, when the emission assessment has to be timely and reliable.

5.2. Indirect Emission Assessment through Energy Efficiency Monitoring

Energy efficiency and powertrain losses are closely related to indirect emissions related to NEVs [49]. Multi-sensor fusion has been utilized to track indicators that are related to efficiency by correlating electrical input, mechanical output, and thermal dissipation. This way, it is possible to see abnormal energy loss due to component deterioration, poor control measures, or unfavorable environmental conditions.

Fusion-based efficiency monitoring offers a more detailed perspective of the same impact of emission than single measurements, in that it considers multi-domain interactions in the powertrain [50]. This combined viewpoint is beneficial to the analysis of vehicle performance across various driving cycles and usage behaviors that can help to make the lifecycle emission estimates more precise.

5.3. Emission Monitoring in Hybrid Powertrain Systems

Hybrid electric cars have some special needs with respect to emission monitoring since they have several propulsion modes and their state of operation often changes rapidly [51]. The level of emission in hybrid systems depends on the interaction of the electric and combustion subsystems, battery states, and thermal conditions. Multi-sensor fusion methods can be used to combine electrical systems, thermal systems, and engine-related data to give a single representation of emission behavior.

Combining information between subsystems, monitoring systems are able to provide a cumulative effect of the emission impact of hybrid operation and determine when things become more emissive [52,53]. These features are critical to realize more efficient energy management plans and adherence to the emission control regulations in actual driving settings.

5.4. Emission-Related Monitoring in Fuel Cell Powertrains

Electric cars powered by fuel cells also need special emission monitoring methods to consider the electrochemical processes and the behavior of the auxiliary systems [54]. Though fuel cells do not generate typical emissions of exhaust gases, the hydrogen leakage, lack of efficiency in energy conversion, and byproducts of degradation may affect the environment and safety. To monitor such phenomena relating to emissions, multi-sensor fusion techniques have been used to combine gas, pressure, temperature, and electrical measurements.

Fusion-based monitoring enhances the observation of abnormal conditions and aids in measuring the efficiency of the fuel cell system with time. Sensor fusion helps add to more dependable diagnostics of fuel cell powertrains with respect to emissions through capturing the interactions between chemical, thermal, and electrical domains.

5.5. Integration with On-Board Diagnostics and Regulatory Frameworks

The growing combination of emission monitoring, onboard diagnostics, and regulatory compliance systems poses new requirements on monitoring methodologies. Multi-sensor fusion facilitates stronger and better estimation of indicators of emission-related information to aid in compliance checks in various operating environments. Fusion-based methods increase the reliability of the diagnostic results by eliminating the sensitivity to the malfunction of separate sensors and increasing the fault tolerance.

In addition, emissions monitoring based on fusion can support such innovative regulatory ideas as real-world emission evaluation and continuous compliance verification [55]. These are in line with the new tendencies in data-driven and performance-based regulatory models in the automotive industry.

5.6. Challenges and Practical Considerations in Emission Monitoring Applications

Although the advantages of multi-sensor fusion as an emission monitoring method have been proven, a number of issues may still be encountered. The balancing of estimation accuracy and computational efficiency must be done with caution in real-time implementation, especially when it is needed by onboard applications with limited resources. In cost-restricted vehicle platforms, the availability as well as reliability of sensors also affect the viability of fusion-based monitoring [42].

Moreover, the changeability of the driving conditions and user behavior creates uncertainty, which should be successfully addressed. To overcome these difficulties, it is necessary to use adaptive fusion algorithms that would ensure a stable state of operation in a vast spectrum of operating conditions. Further research in this direction is necessary to translate the fusion-based emission monitoring methods that are studied in the lab to large-scale use in industries.

6. Applications in Powertrain Health Monitoring

The health monitoring of the powertrain is a key to the safety, dependability, and economic feasibility of new energy vehicles [12]. Electrically charged parts of a powertrain are vulnerable to the complicated processes of degradation based on electrical load, temperature variations, mechanical forces, and external factors. Multi-sensor fusion offers a useful solution to the potential to combine heterogeneous information and improve the level of fault detection, state estimation, and prognostics. In this part, the paper will examine some application areas where sensor fusion has been used to monitor the powertrain health of NEVs.

6.1. Fault Detection and Diagnosis in Electrified Powertrains

The prevention of catastrophic failures as well as the minimization of downtime in NEV powertrains requires early detection and correct diagnosis of faults. Multi-sensor fusion has been extensively used to enhance fault detectability through the integration of complementary data obtained using electrical, thermal, and mechanical sensors [56]. The voltage, current, and temperature measurements can be fused in the battery systems in order to detect short circuits within the battery, cell imbalance, and thermal events that might not be apparent based on separate measurements.

In the case of electric motors and power electronics, the combination of vibration, acoustic, electrical, and thermal measurement data helps in the detection of incipient faults like insulation degradation, bearing wear, and semiconductor degradation [57]. Fusion-based diagnostic systems are capable of differentiating the normal deviations during normal operation and fault-related deviations, which minimizes false alarms and enhances confidence in diagnostic systems under actual operating conditions.

6.2. State Estimation and Degradation Tracking

Good estimation of internal states is one of the cornerstones of powertrain health monitoring. Most health-related variables, including battery state of health, internal resistance, and degradation rates, cannot be measured and have to be estimated using the sensor data. Multi-sensor fusion allows making state estimates more reliable due to the ability to utilize the correlations between different measurements and ensure that the drawbacks of the individual sensors are addressed [34].

The combination of electrical and thermal measurements in battery health monitoring enhances the observability of aging effects and can be used to track the degradation processes continuously [28]. Likewise, with motors and power electronics, a combination of electrical, temperature, and mechanical performance indicators will be a better representation of component health. Such fusion methods assist in health-conscious control measures and ease in prompt maintenance action.

6.3. Prognostics and Remaining Useful Life Prediction

In addition to the fault detection and state estimation, prognostics targets to forecast the future dynamic of component health and determine the remaining useful life [58]. Multi-Sensor fusion is also a key component of prognostic modeling in that it offers rich multi-dimensional input data which reflects the current state as well as the past degradation trend. Combining the information over time and sensing modalities, fusion-based prognostic models are capable of achieving a more accurate representation of the stochastic and nonlinear character of degradation processes.

Remaining useful life prediction, which is based on learning and involves the use of temporal trends in multi-sensor data to predict future performance, has also been applied more often[59]. Combined system. The hybrid prognostic models combining physics-based degradation models with data-driven learning can improve prediction accuracy and controversy, especially in different operating conditions.

6.4. Health-Aware Control and Predictive Maintenance

Multi-sensor fusion not only sustains the monitoring and diagnostics, but also facilitates health-conscious control and foreseeable maintenance plans. Fusion-based monitoring systems will be able to communicate real-time estimates of the health conditions of components to control algorithms that will adjust operating strategies to reduce degradation and increase component longevity. Examples are changing battery charging and discharging profiles depending on the thermal and aging conditions, or changing operating points of motors to alleviate mechanical stress.

Fusion-based health assessment is beneficial to predictive maintenance strategies, as the maintenance actions are planned based on the value of the actual component condition instead of the time period. A conditional approach saves on maintenance costs, increases the availability of vehicles, and improves safety. Aggregated fusion-based health data can be used at the fleet level to aid in asset management and the analysis of reliability[60].

6.5. Challenges in Practical Health Monitoring Applications

However, although much progress has been made, fusion-based powertrain health monitoring in NEVs has a number of challenges that prevent its widespread use. The changing nature of the operating conditions and patterns of use adds uncertainty that makes the modeling of degradation and prognostic prediction difficult. The aging of sensors and sensor failure may also cause a reduction in the accuracy of monitoring unless it is carefully considered in the fusion model[61,62].

Complexity of fusion algorithms that can be implemented on board comprises are also restricted due to computational constraints and real-time requirements. It is also observed that the demand for explainable and verifiable monitoring solutions is gaining an eminent value, especially in applications with high stakes. The solution to these challenges is further studies on efficient, dynamic, and understandable fusion approaches.

6.6. Implications for NEV Reliability and Lifecycle Management

The use of multi-sensor fusion in the powertrain health monitoring is associated with great relevance to the NEV reliability and lifecycle management[6,63]. Fusion-based monitoring systems help to improve the safety, decrease the downtime, and optimize the maintenance planning by providing the opportunity to detect the fault early, estimate the state correctly, and rely on the prognostics. These advantages serve the larger interests of sustainable transportation since they increase the longevity and efficiency of the NEV powertrains.

With the further development of NEV technologies, the use of multi-sensor fusion in health monitoring is going to grow even more. A combination of health monitoring and emission assessment, energy management, and smart control systems is one of the directions of future research and industrial practice. Representative applications of multi-sensor fusion in emission and health monitoring are summarized in **Table 4**.

Table 4. Summary of multi-sensor fusion applications in emission monitoring and powertrain health management for NEVs.

Application Domain	Target Component	Sensor Types	Fusion Approach	Monitoring Outcome
Emission estimation	Hybrid powertrain	Electrical, thermal	Model-based fusion	Indirect emission assessment
Efficiency monitoring	Battery and motor	Electrical, mechanical	Feature-level fusion	Energy loss identification
Fault diagnosis	Motor and inverter	Vibration, current, temperature	ML-based fusion	Early fault detection
Health prognostics	Battery system	Voltage, temperature, impedance	Hybrid fusion	RUL prediction

7. Conclusions and Future Perspectives

This review has considered the importance of multi-sensor fusion methods in measuring emissions and health of powertrains in new energy vehicles and how the latter techniques are increasingly gaining significance due to the emergence of electrified transportation systems. With the growing intricacy and strong integration of NEV powertrains in the electrical, thermal, mechanical, and chemical spheres, the historical system of singly-sensed or singly-modeled monitoring is no longer applicable to satisfy the needs of accuracy, robustness, and reliability. Multi-sensor fusion has been an enabling technology to solve such problems by combining heterogeneous information to give a more dynamic and complete picture of the system behavior.

In the view of emission monitoring, sensor fusion allows estimating the indirect and non-exhaust emission-related indicators, which are not directly measurable. Fusion-based methods combine electrical, thermal, mechanical, and environmental measurements to assist in real-time evaluation of energy efficiency, power losses, and performance degradation due to the degradation of a wide variety of NEV architectures. These abilities are especially useful in the case of hybrid and fuel cell-powered vehicles, whereby the nature of emissions is shaped by a combination of various sources of energy and operating conditions. The connectedness to onboard diagnostics and regulatory frameworks is another indicator of the topicality of fusion-based emission monitoring in real-life implementation.

Multi-sensor fusion has proven to have great advantages in the fault detection, state estimation, and prognostics in the powertrain health monitoring domain. The combination of the complementary sensor signal improves the observability of internal states and degradation of batteries, electric motors, power electronics, and auxiliary systems. Fusion-based monitoring assists in predicting the remaining useful life by allowing for the detection of faults early and being useful in the health-aware control and predictive maintenance methods, which enhance safety and lower operational cost, and increase component life. These developments help directly to enhance the reliability and lifetime management of NEV powertrains.

Even though significant strides have been made, there are still a number of issues that need to be overcome before multi-sensor fusion methods can find full and extensive implementation in the industrial NEV. Problems with sensor cost, data quality, and long-term performance remain a problem for the performance of monitoring. The reality based on heterogeneity and uncertainty of the actual operating conditions creates further challenges to model generalization and robustness. In addition, onboard computational limitations and real-time needs require effective fusion algorithms that both maintain accuracy and are realistically feasible. The necessity of transparency and trustworthiness in the fusion-based decision-making is further emphasized by the increasing need for explainable and verifiable monitoring solutions.

In the future, it is possible to outline several good research directions. Multi-sensor fusion and digital twin technologies present a strong concept of closed-loop monitoring and predictive analysis by integrating real-time data with high-fidelity system models. The advancements made in explainable artificial intelligence can enhance the interpretability and acceptability of the fusion approaches based on data in safety-related systems. Scalable and collaborative monitoring of vehicle fleets supported by edge and cloud-assisted fusion architecture can help to optimize the system at the system level and ensure regulatory compliance. Moreover, the integration of emission monitoring and health management in the same unified fusion systems is another significant chance of having complete powertrain optimization.

Finally, multi-sensor fusion is an important enabling technology towards the realization of precise, robust, and intelligent monitoring of emissions and powertrain health of new energy cars. Further interdisciplinary studies and association with the industry will be necessary to help translate the progress in methodology into useful, deployable solutions. With the ongoing changes in NEV technologies and regulatory demands, it is predicted that fusion-based monitoring systems will become even more central to enabling sustainable, safe, and efficient electrified transportation.

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