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Chapter 8: Intelligent vehicle health monitoring through engine data, artificial intelligence, and machine learning

8.1. Introduction

Data rejection and filtration are required in this step to remove outliers and noise, to get a realistic picture of normal behaviour. The output of a health monitoring system is usually a numerical quantity or an indicator that quantifies the condition of the monitored system's component or subsystem. Different conditions can be represented by different values of such indicators. These features capture higher-level information in the sensor data. The parameters acting as condition indicators for faults are identified and monitored to detect, identify, and characterise faults by studying anomalies and trends. Diagnostic processes allow the rapid determination of specific components that need to be replaced during maintenance. Prognostic processes enable the prediction of the residual life of components by analysing trends in historical observations. A scheme capable of performing fault detection and identification has to be developed first. In case faults are identified, isolation schemes should indicate the degraded subsystem or part of the system which is affected by the fault. Finally, a set of different nudges has to be identified and assessed, regarding the more or less strong deviation from expected performance that is introduced by the fault and its progression. This assessment has to be performed either by making direct use of a generic degradation model or by employing machine learning techniques.

Once the health indicators for all characteristic faults of each critical subsystem of a vehicle have been clearly identified, artificial intelligence techniques can be employed to identify trends, gain insights from the massive volume of data, and make inferences from them. Machine learning refers to techniques designed to take in information and learn from it. These systems have the capability to evaluate and categorize received data and draw inferences from the data. A diagnostic system based on machine-learning techniques has the capability to automatically detect the best predictors of system failure. An intelligent vehicle level health management would require a robust reasoning system that could clearly distinguish between the different layers of the vehicle. Since the various subsystems of an APC have unique health indicators, suitable algorithms must be chosen for data processing, feature selection, and extraction. The choice of algorithm would be based on the requirements of the system and the data being processed for insights.

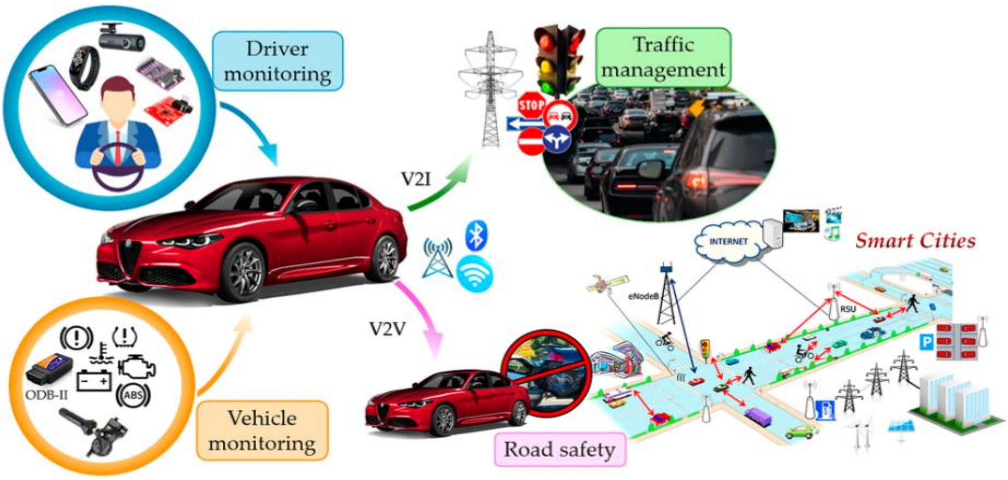

Fig 8.1: Innovative Driver Monitoring Systems and On-Board-Vehicle Devices

8.1.1. Research design

This section outlines the research methodology, including the research questions and hypotheses, the sampling technique and selection of the sample, research design, research instrument, pilot study, data collection procedure, and data analysis technique. The research was aimed and focused on a better understanding of intelligent vehicle health management using engine data and AI techniques. The primary objective of the research was the utilization of the optimum method to estimate the TRP of the engine along with the experimental set-up of data acquisition for running an IC engine as inputs for model formation of the intelligent vehicle health management system. The study firmly aims to utilize data preprocessing techniques, feature extraction techniques, and optimum feature selection techniques. It was planned and implemented to compare the performances of machine learning techniques that predict the TRP of the engine accurately and efficiently. A couple of weeks before conducting the full study, 5 respondents were given a pilot test of the research instrument on some selection parameters of the sampling design. Based on their suggestions, the research questionnaire was modified. The research was conducted using an online survey that best reached the respondents of the study. The statistical analysis in the present research included frequency distribution, graphing, descriptive analysis, data screening, reliability analysis, normality analysis, and correlation analysis. The selected machine learning techniques were implemented on the collected data to create regression models that predict the TRP of both new and old engines accurately.

Data rejection and filtration are required in this step to remove outliers and noise. If the data have come from different sources, these will also need to be combined. Instead of feeding sensor data directly into machine-learning models, it is common to extract features from the sensor data. In the next step, the parameters acting as condition indicators for faults are identified and monitored to detect, identify, and characterise faults. Diagnostic processes allow the rapid determination of specific components/systems that need to be replaced during maintenance . Prognostic processes enable the prediction of the residual life of components/systems. Once the health indicators for all characteristic faults of each critical subsystem of a vehicle have been clearly identified, artificial intelligence techniques can be employed to identify trends and gain insights from data. Machine learning is a subset of AI designed to take in information and learn from it. A diagnostic system based on machine-learning techniques has the capability to automatically detect the best predictors of system failure. An intelligent vehicle level health management would require a robust reasoning system that could distinguish between the different layers of the vehicle. Suitable algorithms must be chosen for data processing, feature selection, and extraction. The choice of algorithm would be based on the requirements of the system and the data being processed for insights.

8.2. Background and Motivation

Modern vehicles are fitted with a number of sensors generating a wide range of data, ranging from low-frequency data representing system control signals, to mid-frequency data representing vehicle environment and state, to high-frequency data indicating system health problems. It is the processed data, rather than the raw sensor data, that provide more relevant, reliable assessments of the vehicles and their subsystems. Advanced Data Processing and Analysis (DPA) techniques are required to filter, process, and extract information from the raw data, which can then be used for vehicle performance benchmarking, safety evaluation, and health condition monitoring. There are three main layers of data processing: (1) data rejection and filtration, (2) data processing and feature extraction, and (3) data analysis. Data rejection and filtration are required to remove outliers and noise rarely seen in normal operating scenarios of the vehicle, to get a realistic picture of the normal behaviour. Various techniques need to be employed to check signal validity and condition, and if erroneous data are found based on threshold limits or statistical distributions, they are removed. Meanwhile, basic transformations are performed to get the data in a more manageable format and improve their reliability in the later analysis processes. For example, the data may need to be time synchronized and resampled according to a uniform sampling interval, or converted to percentage values from raw voltage levels.

Features are extracted from the sensor data, capturing a number of higher level information from the raw data points, such as moving averages, signal decomposition, frequency content, and so on. They should be data-driven indicators with good adherence to the behaviour that is being monitored, hence able to detect subtle/hard to predict anomalies that other datasets or methods may ignore or fail. Prior to implementing a modelling approach, a number of parameters acting as condition indicators for the specified faults need to be identified, preferably on both a physical/engineering basis and also on a data-driven basis. These condition indicators are then monitored to detect, identify, and characterise the faults by studying anomalies and trends in new observations of history or monitoring data. A diagnostic process allows for determining specific components needing replacement during a given maintenance interval at an engineering level, in addition to improving on-board understanding of the vehicle and factors causing premature failure. A prognostic process enables the prediction of the residual life of components/systems by analysing trends in historical observations. Obtaining insights and making inferences from the health indicators for faults of critical subsystems of a vehicle using Artificial Intelligence (AI) techniques can be another layer of abstraction above the data processing/feature extraction. These health indicators vary greatly from data types and types of faults, e.g. frequency characteristics for bearing and high-frequency values for excessive friction and wear, and can be mapped to different AI techniques for data analysis, gain insights and reasoning. Machine learning is a collective term applied to a range of techniques designed to learn from information within a specific domain, e.g. grouping, classification, regression, trend/exemplar analysis, rule derivation, and inference.

8.3. Engine Data Acquisition

Intelligent health state monitoring of advanced powertrains can be accomplished using de-centralized monitoring through the on-board data logging of condition monitoring systems that can provide early indication of developing faults. These systems can be based on inexpensive on-board data loggers acquiring engine data for data rejection and filtration for noise removal and outlier rejection to get a realistic picture of the normal operation. The filtered data can then be stored on-board and downloaded onto a cloud server from where it can be accessed for assessment of powertrain health. Intelligent algorithms such as artificial neural networks, support vector machines and decision trees can be trained with past fault occurrence data to detect and predict likely future occurrence of faults. Further, use of multiple data loggers can provide intelligent health state monitoring for vehicle level and subsystem level conditions through estimating health states with linkage to both knowledge-based and data-based systems.

In automotive applications, a variety of sensors are typically used, such as position, speed, temperature, pressure and flow-rate sensors. Instead of feeding the raw sensor data directly into the machine-learning models, it is common to extract features from the sensor data. The raw sensor data contain information from different sources, and the feature refinement stage allows for extracting such information and generating features that are relevant for the following processing.

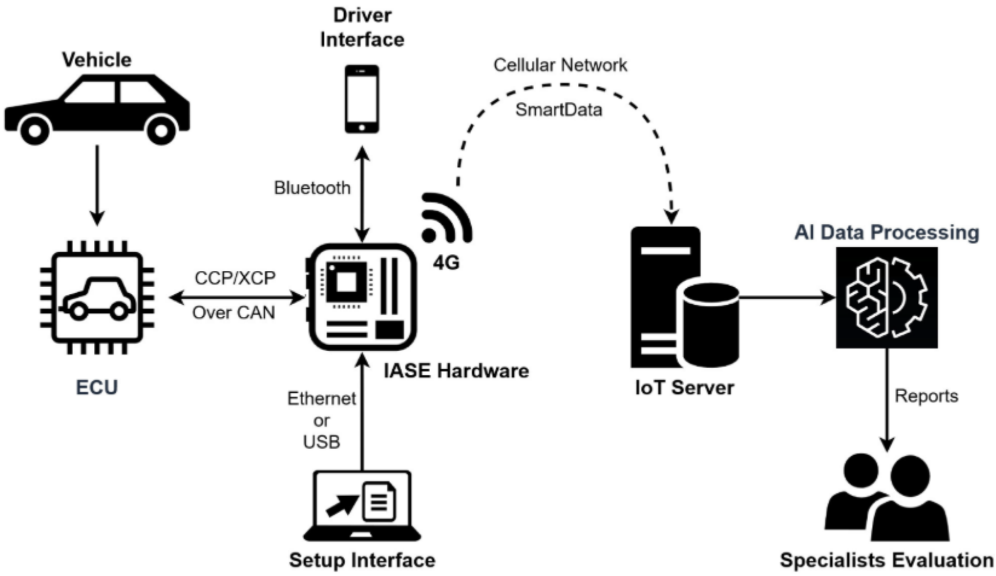

Fig 8.2: Data Acquisition System

8.3.1. Types of Engine Data

A vehicle generates vast amounts of data through sensors and ECUs already built into the vehicle. This data is thought to contain a wealth of information regarding the HMI of the vehicle, including UXV (Unmanned Ground Vehicle) configuration status, component performance, and future failure of components. The vehicle data can be classified into CAN (Controller Area Network) data, personal data, and the context of these events, which are described in words. CAN data and personal data are structured data, which are recorded in a predetermined format. The context data may include free text input, voice command results, and multi-sensory event timeline captured data, which is more generic.

Some of the CAN data such as GPS data and battery voltage are already available in standard form, while some other types of CAN data depend on the actual implementation of the subsystem. CAN data can be classified into three groups: vehicle state, driving behaviour, and component data. For example, a gear shift can be detected when the vehicle speed does not change with time for a fixed period but the throttle position changes from being fixed to 100% or 100% to being fixed for a certain duration. A case where the vehicle accelerates and decelerates in a short period by more than a threshold can be marked as aggressive driving behaviour. By examining the amounts before and after the sudden change compared to the previous average amounts, driving habits such as hard breaks or accelerating can be detected.

8.3.2. Data Collection Methods

Currently, each vehicle is equipped with sensors for Enhanced Vehicle Health Management (EVHM) and Intelligent Vehicle Health Management (IVHM). The data collection methodology can be divided into two categories: (1) vehicle-level sensor data when the vehicle is in operation, and (2) component-level data collection using devices like an oscillograph when the vehicle is stopped . The most commonly used sensor parameters from the vehicle are the engine parameters, which form the basis of this chapter.

The vehicle engine's data are collected through an On Board Diagnostics (OBD) II port. An engine's performance parameters such as MAF and RPI can be collected from vehicles equipped with specific IC engines. Most of the modern-day vehicles come equipped with a Vehicle Area Network (CAN), which is accessed using a mini USB interfacing device for data collection. The engine health parameters in the form of physical units can be derived from the CAN values using a conversion algorithm. The onboard parameters such as RPI, RPM, and MAF are recorded using a CAN-OBD-II device. Data is collected at a sampling frequency of 1 Hz during running conditions.

Data rejection and filtration are required to remove outliers and noise. If the data have come from different sources, these will also need to be combined. Instead of feeding sensor data directly into machine-learning models, it is common to extract features from the sensor data. In the next step, the parameters acting as condition indicators for faults are identified and monitored to detect, identify, and characterise faults by studying anomalies and trends. Diagnostic processes allow the rapid determination of components/systems that need to be replaced during maintenance and can also contribute to understanding the factors causing any premature failure. Prognostic processes enable the prediction of the residual life of components/systems and the most likely failure mode by analysing trends in historical observations. Once the health indicators for all characteristic faults of each critical subsystem of a vehicle have been clearly identified, artificial intelligence techniques can be employed to identify trends and gain insights from the data. Machine learning refers to techniques designed to take in information within a specific domain and learn from it. A diagnostic system based on machine-learning techniques has the capability to detect predictors of system failure by detecting failure patterns in the training dataset. Intelligent vehicle level health management requires a robust reasoning system that could distinguish between the different layers of the vehicle and accommodate data from multiple systems. Suitable algorithms must be chosen for data processing, feature selection, and extraction based on the requirements of the system and the data being processed.

8.4. Artificial Intelligence in Vehicle Monitoring

Artificial Intelligence (AI) offers advanced techniques to gain insights from data and draw inferences from information (Automotive World 2024; Axios et al., 2024; KnowledgeAgent 2024). Ultimately, the purpose of data analytics is to take inputs one step further to identify and assess trends. A machine learning scheme takes information that falls within a defined domain and learns from it. Noticing that a certain scenario matches an input in memory, the process looks for the most appropriate output. The learning occurring during this process helps to both build and refine the representation of data. An intelligent system at the vehicle level aims to optimize preventive maintenance. It would require a reasoning system that was capable of distinguishing between layers at different levels of abstraction. At least three possible layers: the vehicle, sub-systems, and components; each layer has its own characteristics. Suitable algorithms for data processing, feature selection, and extraction must be chosen to fit the technology-based requirements and information-based nature.

For an intelligent Vehicle Health Monitoring (VHM) System (IVA), it must first be established what the aged/used-up/near-failure state of the component/sub-system is compared to the relatively new state. Tools such as physical models of the system, leading to statistical models, simulations, and data analytics can extract behavior as a function of time. After identifying parameters, stored data acquired during normal conditioning tracking parameters must be analyzed to build and extract models. Model fitness describes the model's behavior in terms of the fitted coefficients, which must be used for tracking. Calibration of the model can achieve precise coefficients. Sensors can be analyzed to identify the most sensitive in fault detection. These parameters can be monitored to detect and characterize faults by isolating deviations of the system behavior from the expected/normal performance.

8.4.1. Overview of AI Techniques

The newly emerging industry of intelligent health monitoring for vehicles is an interdisciplinary domain where vehicular field data, together with vehicle data, need to be combined and analysed using artificial intelligence (AI) techniques. Normally, when a project is conducted in this domain, the first step is to determine check boxes such as what type of sensor data the vehicles emit, how frequent these signals are obtained, what vehicle data should be captured, and how frequent these messages should be logged. The next step is to determine a cloud platform or on-prem solution to receive this data from vehicles and have a pipeline to query this data before applying AI techniques to it. This stage requires expertise in vehicular networks and data management. The next stage is the application of AI techniques to the vehicular field data and vehicle data received in the last step. This is the main engineering task, and there are several options available, such as health monitoring based on supervised classification techniques, survival analysis, or unsupervised anomaly detection methods. Over the last few years, intelligent vehicle health monitoring has become one of the main trends of the automotive industry. As more and more vehicles are produced, the volume of the vehicular field data rapidly increases, posing challenges to traditional post-hoc data analysis methods. New AI methods are required to automate the workflow and obtain insights from vast amounts of vehicular data. From a data engineering point of view, the workflow of intelligent vehicle health monitoring consists of four major stages. The first consists of a pipeline to receive the vehicular field data and vehicle health-related data in cloud storage format. Data typically streamed from vehicles may be in a standard format such as .json or .parquet, and land in cloud storage. The second stage is data processing to convert the raw data to a consumable format by AI techniques. Data rejection and filtration are required in this step to remove outliers and noise. Instead of feeding sensor data directly into machine-learning models, it is common to extract features from the sensor data. Commonly used features for the prediction of system health are frequency based features, time-based features, wavelet transform features, and long-term Fourier transform features. A list of well-established features is available, and domain experts can also suggest custom-made ones. In the next step, the parameters acting as condition indicators for the faults are identified and monitored to detect, identify, and characterise the faults. Diagnostic processes allow the rapid determination of the specific components/systems that need to be replaced during maintenance. Prognostic processes enable the prediction of the residual life of components/systems and the most likely failure mode by analysing trends in historical observations. AI techniques can be employed to leverage their ability to identify trends, gain insights from the massive volume of data, and make inferences from them. Therefore, this stage accepts data in the consumable format processed in the last stage and applies AI techniques to it.

8.4.2. Role of AI in Predictive Maintenance

Condition monitoring identifies the operating condition of devices based on online measurements (OpenXcell et al., 2024; Reuters et al., 2024). CM techniques can be divided into two groups. Vibration-acoustic analysis, infrared monitoring, and model-based condition analysis are features that traditional techniques fail to provide. New techniques, which are developed in the context of IOT, are more reliable due to their independence of device behavior and not affecting operation past the installed sensors. However, as with all efficiencies achieved with new tools, this comes with a trade-off in complexity and increased need for data processing. In addition, proper handling of the IoT is critical to a successful setup. Data processing and analysis in condition monitoring is achieved with modern ML methods, which implement high-quality intelligent algorithms with the ability to recognize complex data patterns.

ML is able to automatically analyze massive amounts of data thanks to their innate algorithms. In comparison with traditional procedure-specific methods, ML analyzes big data and finds hidden correlations. These data can be complex, consisting of images and curves, and generated in a constantly changing environment, such as heavy industrial tasks involving mining, construction, or the automotive sector. This paper aims to define the common definitions of PdM, the use of measurement sensors, and the mainstream ML models. Various applications in static and dynamic devices are also given. Challenges that PdM faces are also analyzed, focusing on the core question: how to obtain quality data for implementation.

With IoT data and ML analysis techniques, PdM has excellent potential for further growth and increased market penetration. With developments in IoT and data analytics techniques, as well as component evolution itself, predictions will become more precise and trustworthy. However, employing ML in PdM, as with any sophisticated analysis technique, follows a systematic process in stages that need to be executed correctly to achieve proper prediction and a successful return on investment. This process is represented by a PdM deployment overview chart which clearly delineates the pre-processing of historical data recorded in varying conditions during past working cycles. Data collection through sensors installed on devices which form a PD, gathering IoT networks is essential in this context. LW should typically comprise several sensors which report their measurements through a common unit, measures, and analysis steps performed on aggregated datasets, creating valuable datasets for application to an ML model. ML models performance is tightly connected with the quality of data.

8.5. Machine Learning Algorithms

From the perspective of machine learning algorithms, four techniques are proposed including K-Nearest Neighbors (K-NN), Support Vector Machines (SVM), Decision Trees (DT), and Artificial Neural Networks (ANN). This section describes the algorithms to implement.

8.5.1. K-Nearest Neighbors:

K-NN is one of the basic classifiers based on the instance theory. It classifies the test samples according to the labels of K samples nearest to it from the training samples. - Prediction: The built model does not have existing classifiers, and all of the training samples are stored in the model database. All samples have the same weight, and their classification is determined by calculating the distance to the sample that is nearest to the test sample in the feature space, and the attribute with the smallest distance is selected. The parameter K is defined for the classification of cases with identical distances. For samples that belong to a variety of labeled classes, samples belonging to different classes are assigned weights based on their distances, that is, the closer they are to the samples the greater their weight.

8.5.2. Support Vector Machines:

SVM classifies data using hyperplanes in a good way. It measures the distance between the hyperplane and the nearest data points from both of the classifications, and searches for a hyperplane with the maximal margin. SVM draws the decision boundary by creating a hyperplane for separable cases (there can be an extreme measure of the gap of data points of both classes; the case is in the linear separable case). If a hyperplane is drawn, its unique optimization can classify all points. It can also be controlled to accept some points wrongly classified and furthermore analyze the structure of the data (reflected by the orthogonal distances from nearest points to decision boundary). By introducing the slack variable, SVM allows the consequence to be classified badly on purpose to a certain degree. The non-separable case is also one of the important features (it maps data points into another space with a high dimension where they might be easier to separate).

In the presented preliminary work, an intelligent health monitoring system is proposed for a vehicle based on artificial intelligence and machine learning techniques. The process is explained along with the various data processing steps involved in developing the intelligent system. In addition to the proposed techniques, a detailed analysis of the historical data from the health and usage management system was performed to identify the parameters that behave differently under faulty conditions and could serve as good health indicators. These parameters are classically monitored to develop a vehicle-level health monitoring and management system.

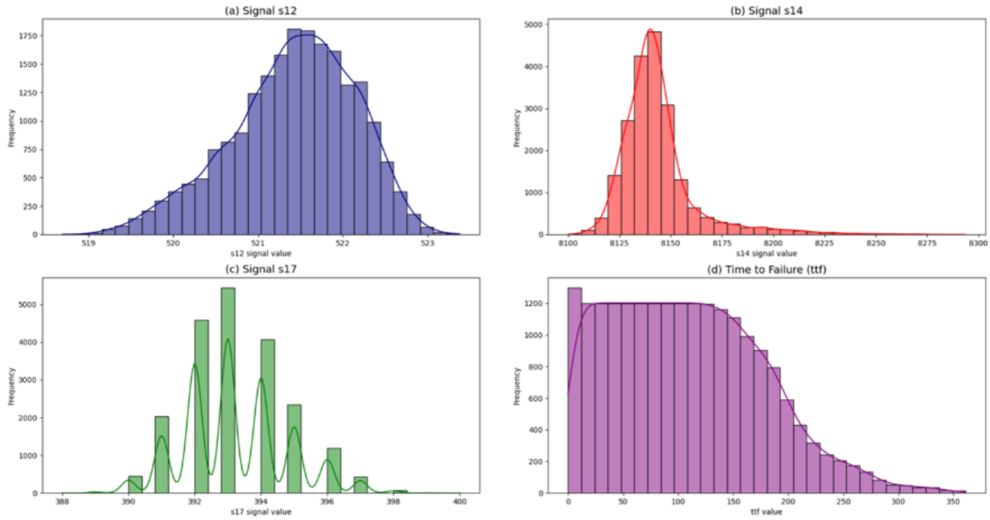

Fig : Data-Driven Engine Health Monitoring with AI

8.5.3. Supervised Learning Techniques

Each Artificial Intelligence (AI)/Machine Learning (ML) technique tackles the data mining task in a different manner, which should also be a consideration before the technique selection. It is often important to know whether the chosen techniques can handle the problems at hand. Different constraints such as time, interpretability and performance may come into play whilst making this selection. The main types of data mining techniques are:

1. Supervised learning techniques: Techniques in which a training set of data with an additional output variable is fed into the model which learns to make predictions for unseen inputs. These inference models can take many forms depending on the underlying mathematical approach.

2. Unsupervised learning techniques: Techniques which are based on the inputs only (without outputs), so presuming no knowledge of the system. These models extract insights from the data without a specific target in mind. Thus, these models tend to be exploratory rather than predictive. Clustering, anomaly detection and matrix factorization are the main categories of unsupervised techniques.

3. Semi Supervised learning techniques: Techniques which combine the two previous kinds of models. Supervised models are usually more reliable, though often come with high overhead costs associated with labelling much data. Hence some training data may

be reserved for an unsupervised model, which the supervised model would need and be validated against. There are a wide variety of semi-supervised techniques.

4. Rules extraction techniques: Techniques which generate a small number of interpretable conditions for the inference model output (as opposed to continuous prediction). Output can then be presented in lay terms instead of numerical values which may not be interpretable to a human. The process of generating rules and thus accepting the model is usually computationally expensive and added to the response time.

8.5.4. Unsupervised Learning Techniques

Generally, there are two categories of machine-learning techniques; supervised and unsupervised techniques. The first category requires a labelled dataset with ground truth where features and target values of the data need to be provided. Such models first learn from numerous examples during the training phase, and they use this information to predict the output values when deployed in a real environment. In the second approach, a model is trained with an unlabelled dataset which consists of only input features. The model learns a profile of the data and detects outliers or samples behaving differently compared to the normal behaviour of the vehicles. Unsupervised learning techniques are used to create a standard profile of normal behaviour, track the latest behaviour of the vehicle and potentially detect if a sample appears to be abnormal, i.e., not adhering to the learnt standard. By creating an estimated output from the features acted upon by a mathematical transformation, the predicted output can be compared to the actual output as a simple error value.

Association Rule Learning is one of the classic techniques in machine learning that finds relevant dependencies of events described by simple facts stored as observations in a database. A successful association-rule discovery application analyses retail sales transactions and identifies what products are frequently bought together. The counterpart for vehicular data, where each data point consists of parameters of a single vehicle, time, and value, can find out correlations of different parameters in the same data point, identify clusters of parameters tracking similar patterns, and discover what parameters change together over time or with other parameters. Discovering spatial and temporal correlations at different resolutions can also be filtered and represented as a GIST, stored and displayed as a temporal GIST snapshot, latency in time, and regions. Other classic data-mining techniques for vehicular data can be employed, such as non-parametric clustering to segregate clusters in the parameters before applying classification algorithms.

8.6. Conclusion

The above-mentioned features are examined statistically to analyze how the characteristics would change over time during a failed state. After examining the standard deviation, skewness, kurtosis, coefficient of variation, and linear slopes of the features, it is observed that the decision variable of the confidence mechanism provides the most promising results. As some of the features can exhibit abrupt changes or sudden spikes or dips while changing into a failed state, a simple one-stage thresholding algorithm would fail to detect such patterns. Therefore, a multi-layered decision mechanism is proposed to differentiate between the healthy and faulty conditions, while employing a suitable tapering function to reduce the false alarms. The sigma-decision layer is a nonlinear approach that could successfully account for sudden changes and detect only the faults with a long time horizon. The quantified health of the vehicle is very useful in determining the priority of the monitored health parameters in a vehicle health management and maintenance system.

The proposed intelligent health monitoring system is implemented on actual fleet data obtained from a new generation combat vehicle, and its successful utilization in the field is demonstrated. The main challenges and future work addressing the scalability aspect of the proposed system while retaining its high accuracy are also discussed. Additionally, the still infamous safety-critical aspect of intelligent systems, especially AI-driven ones, is a cause of concern. Vehicle manufacturers can try to develop interpretability approaches to understand the vehicle health diagnostic and prognostic decisions by analyzing lower-dimensional projections of the high-dimensional parameter space.

8.6.1. Future Trends

Intelligent vehicular health management is expected to evolve rapidly with the incorporation of new technologies. Featured additions may include portable telematics devices, new vehicular sensors, and the vehicular internet of things (V-IOT). Today's telematics hardware is designed with new generations of wireless modules with higher speeds and lower costs, such as cellular fifth generation and the upcoming sixth generation and other low-power wide-area network (LPWAN) communication protocols. Integration of portable telematics devices into existing vehicles is expected to flourish due to their affordability and ease of installation.

The latest generation of sensors at affordable prices, especially those employing micro-electromechanical systems (MEMS), may soon be widely incorporated into the health-monitoring system of the vehicle to create a more realistic vehicle health picture with the ability to track a vehicle's driving history and cumulative wear. With increasing connectivity and cheaper sensors, there is a need to refine algorithms for damage estimation and predictive maintenance to use more realistic data. Automated telematics inspections and data collection may replace manual driver inspections with telematics-enabled services and telematics partnerships and collaborations with commercial fleets.

Technologies for real-time individual vehicle health management that have not advanced in the above aspects include mining of various individual vehicle sensor and operational data, failure diagnosis, scene reconstruction, and damage estimation from vehicle-wide in-depth supervised learning to enhance the use of health and usage data for intelligent vehicle fine-grained health and usage management. Meanwhile, regulation and policy development are necessary to ensure fair markets and assist in deploying the vehicle telematics and health management system. Even though the future is unknown, potential trends were highlighted here.

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