An Overview of Telematics-Based Prognostics and Health Management Systems for Commercial Vehicles

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Abstract. Prognostics and Health Management/Monitoring (PHM) are methods to assess the health condition and reliability of systems for the purpose of maximising operational reliability and safety. Recently, PHM systems are emerging in the automotive industry. In the commercial vehicle sector, reducing the maintenance cost and downtime while also improving the reliability of vehicle components can have a major impact on fleet performance and hence business competitiveness. Nowadays, telematics and GPS are used mainly for fleet tracking and diagnostics purposes. Increased numbers of sensors installed on commercial vehicles, advancement of data analytics and computational intelligence methods, increased capabilities for on-board data processing as well as in the cloud, are creating an opportunity for PHM systems to be deployed on commercial vehicles and hence improve the overall operational efficiency. This paper surveys and analyses the nature of PHM as well as progress and challenges towards achieving integrated and intelligent PHM systems for commercial vehicles.

Keywords: Prognostics, Health Management, Telematics.

1 Introduction

Telematics have traditionally been used to track the position of vehicles using the Global Positioning System (GPS), but with the power of cloud data storage and computing, telecommunication and data analytics, various other services such as: fuel saving, fleet performance management, driving behaviour monitoring, dynamic routing, diagnostics and prognostics are being offered by telematics providers. Therefore, the number of fleet operators and Original Equipment Manufacturers (OEM's) that have started to use telematics has increased considerably in recent years. The main aim is to reduce costs and the impact on the environment as well as improving resource productivity, efficiency and asset management.

Moreover, as a result of advances in the automotive industry, commercial vehicles have become more advanced in technology and hence, reliability of individual critical components is an important factor for improving the overall reliability and quality of the vehicle. Commercial vehicle can be defined as "any motorized road vehicle which by its type of construction and equipment is designed for, and capable of, transporting, whether for payment or not: (a) more than nine persons, including the driver; or (b) goods" [6]. Therefore, trucks, coaches, buses, vans and trailers are categorised as commercial vehicles.

Telematics-based on-board tracking systems are comprised of three core parts: a GPS location tracking system, a CAN-bus (controller area network) interface and a supplement data collector. The GPS location tracking system transmits the location of the vehicle at a regular timed interval, distance or after predefined event triggers. The system interface to the CAN-bus is used to read, decode and pre-process the data from the vehicle bus. The supplementary data includes the on-board unit state-of-health, state-of-function data and external information such as ambient temperature.

The server-side of a tracking system is responsible for collecting, processing and storing all data transmitted by the on-board tracking system and displaying the status of the vehicle as well as statistical reports to the users (e.g. fleet managers, fleet operators, and drivers) via a web portal, smart phone apps or in-cab screen. On-board and server side systems can communicate via various networks such as cellular wireless (e.g. 2G/3G/4G) and Wireless LANs.

Recently, Prognostics and Health Management/Monitoring (PHM) is becoming more important to fleet managers because it plays an important role in improving profit margins. PHM systems aim to predict the future behaviour, state-of-health and remaining useful life (RUL) of individual vehicle components based on assessing the current and past health (diagnosis) and future health (prognosis) [26]. The feasibility of designing and implementing PHM systems has increased with the wider availability of low cost and more accurate sensors in commercial vehicles, powerful on-board telematics systems, fast mobile data communication and cloud computing.

PHM systems in commercial vehicles can help to meet several critical goals:

- Eliminate or at least minimise the risk of unexpected breakdowns and unscheduled downtime
- Minimise unscheduled and/or unnecessary periodic maintenance
- Reduce maintenance costs (including spare parts and labour)
- Improve the reliability of the fleet
- Keep the fleet in top performance condition
- Reduce warranty costs
- Improve customer service

On-Board Diagnostics (OBD) systems can be used to evaluate the health of vehicle components. Various legislations state that all manufactured HGV's in Europe after the 1st of October 2006 should be equipped with an OBD system [7]. Therefore, OBD became a standard component of modern vehicles.

This paper conducts a brief literature review of PHM systems in commercial vehicles in order to identify key development and challenges. Section 2 makes a review of the main maintenance strategies and then Section 3 discusses the literature on vehicle predictive maintenance. Section 4 discusses some of the key challenges for the further application of PHM in the automotive industry. Finally, Section 5 looks into the future of telematics-based PHM systems for commercial vehicles.

2 Repair and maintenance strategies

Several maintenance strategies can be identified in the literature and they can be classified into two main types: corrective and preventive. In a corrective, run-to-failure or reactive maintenance strategy, the equipment is repaired after a breakdown or an obvious fault occurs without performing any scheduled maintenance. Within preventive or proactive maintenance strategies, three categories can be identified: scheduled, condition-based maintenance (CBM), and predictive maintenance (PdM).

In scheduled preventive maintenance (also known as time-based or periodic), inspections and (possibly) repairs are performed at specific interval times given by a pre-specified schedule. Time intervals are usually calculated based on age, usage or failure distribution [3]. In CBM, the performance of the system is monitored in real time and maintenance tasks are triggered when some reading measurement goes beyond a predefined limit (threshold) or tolerance. The PdM strategy is based on collecting measurements about the state of the systems in order to analyse and find trends and patterns. This type of analysis is then used to predict the RUL, and hence the degradation and the failure time of the system [4], [9], [13], [21]. The PdM strategy aims to reduce the risk of unexpected failures, which may occur before the next scheduled maintenance, as well as unnecessary scheduled maintenance activities [17]. In fact, CBM and PdM can be considered maintenance strategies of the same type because both are based on monitoring the system status [9]. However, CBM can be considered mainly a reactive strategy while PdM can be considered as a more proactive strategy.

Prognostics usually refers to a process carried out to prognosticate or predict a failure in advance [11]. There are mainly four categories: experience-based, model-based, data-driven based and hybrid [13], [25]. The experience-based or statistical approach is mainly based on historical service failure data and expert judgment for developing a rule-based model. The model-based or physical degradation approach is based on the physical fundamentals of a system. Although, this approach is highly accurate for a specific system, any minor changes in the component and operating conditions require the model to be updated. The data-driven approach requires large amount of historical failure data to capture the system behaviour using data analytics and machine learning techniques. The main disadvantage of this approach is that it highly depends on quality and quantity of historical data [20].

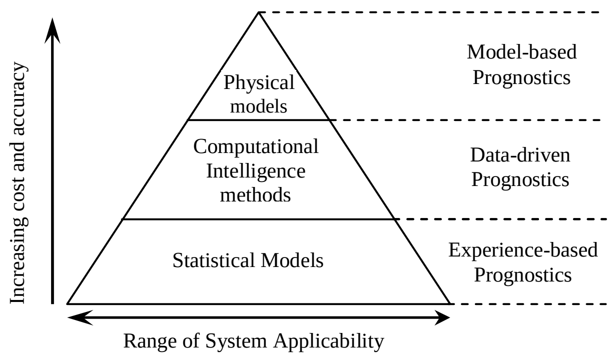

Fig 1 Hierarchy of prognostic approaches

The hybrid approach is a combination of one or more of the other approaches and seeks to benefit from their respective advantages. One of the main applications of the hybrid approach is in multi-component systems. Figure 1 illustrates the hierarchy of these main types of prognostic approaches [19]. The pyramid in Figure 1 indicates that there is a trade-off between the applicability range of the approach and its accuracy and that as expected, the more accurate the approach the more costly it is.

It is beneficial to note that the e-maintenance concept which has recently been discussed several times in the literature refers to the integration of information and communication technologies within the maintenance strategies [12, 24]. Integrated Vehicle Health Management (IVHM) is another concept which is derived from the Health and Usage Monitoring System (HUMS) developed for helicopters during the 1980s and 1900s. The IVHM system is originally designed to determine, verify and solve the aircraft faults [8].

3 An overview of PHM system for vehicle

The amount of literature on prognostics systems for vehicles is much less than on diagnostics systems as many research studies have focused on fault detection in mechanical or electrical components of the vehicle which is mainly of interest to the Original Equipment Manufacturers (OEM's). However, some of the research studies that we have identified in the area of vehicle prognostics systems are discussed in this section.

Grantner et al. [10] introduced a fuzzy model to diagnose the axle fatigue of light trucks with future applications to military ground vehicles. The load stress, the number of cycles of the load stress and previous damage are input to the model. Then, the system predicts the RUL of the axle based on the cumulative damage to the axle, which is given by the fuzzy model. The expert knowledge and linear damage model are used to generate the fuzzy rules and membership functions.

Ahmed et al. [2] designed a discrete hidden Markov model to detect manifold air leakage in the air intake system of gasoline engine and approximate the health status of inlet manifold. The manifold pressure, engine speed and throttle position are used as inputs to the model. They identified four states for different health conditions: a fault free stage, an intermediate fault stage 1, an intermediate fault stage 2 and a fault stage, quantified based as 0%, 4.5%, 9% and 18% of wide open throttle, respectively. Results of the experiment performed on a 1.3L production vehicle engine through On-Board Diagnostic version II (OBD-II) showed that the proposed model can be helpful for prognosis of air leaks.

Byttner et al. [5] presented the consensus self-organised method that aims to find and select related sensor data on each vehicle to be used in detecting faults that are not predefined. The model is generated and adopted on an on-board system while the vehicle is being used. They used the linear principle encoding analysis to reduce the volume of data transmitted from on-board systems to the server. Testing on real data for a cooling system of a city bus showed that their method has the potential to be used for self-discovery fault detection systems.

Zhang et al. [27] proposed the concept of connected vehicle diagnostics and prognostics (CVDP), which has been partially deployed in production at General Motors (GM). This approach aims to demonstrate that fleet-based cross-vehicle analysis can reduce trouble-shooting time by improving root-cause analysis. CVDP remotely and continuously collects vehicle engineering data and turns it into knowledge for the diagnostics and prognostics system. Moreover, CVDP also gathers data from vehicle assembly lines and repair workshops. Then, once the data is verified and validated, system faults are detected and RUL of various components are predicted. It has been reported that the battery monitoring system ECU has been programmed and implemented in production through OnStar [22] system to evaluate the benefits of the CDVP based on current-based and voltage-based algorithms.

Last [17] and Last et al. [18] presented data mining models to predict vehicle failures. Vehicle sensor readings and warranty failure data are used as inputs to single- and multi-target info-fuzzy network algorithms with minority oversampling and majority under-sampling techniques to issue the probability and the timing of as a case study. The data attribute in the model are: state-of-charge, battery age, off asleep amp hours, temperature, amp-hours during ignition off and travelled distance.

Instead of using classical Monte Carlo simulation methods, Abbas et al. [1] used a particle filtering-based approach to predict the failure mode in vehicle electrical power generation and storage systems. The advantages of this approach are that it needs less number of samples and is also capable of dealing with complex nonlinear and/or non-Gaussian cases. Their particle filtering-based approach has been implemented and tested using simulation data to determine the current level of lead-acid battery grid corrosion and determine the probability of the time-to-failure. The Arrhenius degradation model and estimation of internal resistance of battery based on measured voltage and current during cranking are two items required by the suggested method.

An engine oil quality estimation model based on component analysis and statistical analysis methods was introduced by Jun et al. [14], [15]. The model estimates the quality of the oil by analysing its degradation status. To design the model, various relations between engine mission profile data such as mileage, number of engine start-up, etc. and oil quality indicator were studied. As the model only requires the mission profile data, no sampling engine oil is needed. The main drawbacks of the introduced algorithm are that it only focuses on providing oil viscosity indicator and that there is a lack of guidance regarding when oil should be changed.

It has to be noted that as the number of electric and hybrid vehicles increased, PHM of lithium-ion batteries has attracted a lot of research interest in vehicle prognostics systems [23].

4 Challenges

From this brief literature review, there is some evidence that PHM systems are being deployed in vehicles, specifically in commercial vehicles, but very slowly despite the fact that their use could bring considerable cost savings. Some of the main challenges that we believe remain to be tackled are discussed in this section.

In recent years, the electronics control and software (ECS) systems in vehicles have become more complicated and this can bring three main challenges for the development and deployment of diagnostics and prognostics systems:

1. Unexpected new fault root in the interaction between the different components and/or sub-systems
2. Infrequent and intermittent non-identified faults, which can be reported as "No Fault Found"
3. High complexity of predicting the system RUL [27]

As many PHM systems have been developed relatively recently, it is difficult to accurately perform a sound cost-benefit analysis and to identify tangible benefits of implementing such PHM systems. Although increasing the sensitivity of a PHM system can reduce the probability of predicting a potential future fault or failure (true positive), it may also increase the possibility of trigging false alerts (false positive) when the system is in a reasonable good level of state of health. In contrast, if the sensitivity of the PHM system is not high, it is more likely that it will not be able to predict potential failures or faults (false negative). The possibility of giving false positive and/or false negative alerts seems to be one of the main criticisms of PHM systems.

PHM concepts were pioneered in the aerospace industry and then they have been applied in other sectors such as the automotive industry and particularly commercial vehicles. Although deploying PHM on commercial vehicles is creating an opportunity to get benefits with predictive maintenance systems, the accuracy of the system can be affected by the number of sensors that can be located in vehicles, which is significantly less than in aircraft.

PHM methods proposed in the literature often require more sensors with a high level of accuracy and/or computing power than is available on-board today's vehicles [5]. In addition, although most of the published prognostics studies state the intention to actually introduce a prognostic system into operation, the focus has been more on the fault detection and the prognostic system has been left for future work with no much evidence of this being realised yet. Moreover, a very limited number of research studies address the application of prognostic systems in maintenance management [3]. These issues can be resolved by efficient communication among theory developers, practitioners and manufacturers in the area of reliability and maintenance [13].

5 A look to the future

With PHM systems, maintenance work can be scheduled in advance of the failure. The maintenance and downtime therefore become significantly shorter with prognostics relative to diagnostics.

Currently, a large volume of data is being provided by the vehicle's electronic control unit (ECU's) which can be extremely valuable to the process of vehicle health monitoring, but this is not yet widely or proactively used. Typically, each ECU is responsible for its own diagnostics and fault management, which is not beneficial for distributed functions. Moreover, system parameters should be monitored relative to each other. Therefore, an integrated and intelligent approach is appropriate to diagnose and predict system-wide failure in vehicles.

There has been considerable investment in telematics-based business solutions in the last few years. This has increased the pace of development and deployment of telematics-based PHM systems for commercial vehicles as telematics plays a key role in the PHM system. Moreover, in response to the demand for supplying more accurate and extensive data by fleet operators, the OEM's have started installing more advanced sensors in vehicles which can improve the accuracy and precision of future PHM systems.

Furthermore, predictive modelling has started to produce some benefits for fleet operators in various areas such as traffic, available parking spaces and weather. In the coming years, an even wider adoption of this approach could be used to build a better and more efficient fleet in terms of maintenance, routing and scheduling.

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