ARTICLE INFO
Article ID: 03-16-04-0026

doi:10.4271/03-16-04-0026

Driving Behavior Modelling Framework for Intelligent Powertrain Health Management

Aleksandr Doikin,[1] Felician Campean,[1] Martin Priest,[1] Emanuele Angiolini,[2] Chunxing Lin,[2] and Enrico Agostinelli[2]

[1]University of Bradford, UK
[2]Jaguar Land Rover, UK

Abstract

The implementation of an intelligent powertrain health management relies on robust prognostics modelling. However, prognostic capability is often limited due to unknown future operating conditions, which vary with duty cycles and individual driver behaviors. On the other hand, the growing availability of data pertaining to vehicle usage allows advanced modelling of usage patterns and driver behaviors, bringing optimization opportunities for powertrain operation and health management. This article introduces a methodology for driving behavior modelling, underpinned by Machine Learning (ML) classification algorithms, generating model-based predictive insight for intelligent powertrain health management strategies. Specifically, the aim is to learn the patterns of driving behavior and predict characteristics for the short-term future operating conditions as a basis for enhanced control strategies to optimize energy efficiency and system reliability. A case study of an automotive emissions aftertreatment system is used to comprehensively demonstrate the proposed framework. The case study illustrates the approach for integrating predictive insight from ML deployed on real-world trip behavior data, in conjunction with a reliability-based model of the operational behavior of a particulate filter, to propose an intelligent active regeneration control strategy for improved efficiency and reliability performance. The effectiveness of the proposed strategy was demonstrated on an industry standard model-in-the-loop setup with a representative sample of real-world vehicle driving data.

History

Received: 10 Feb 2022
Revised: 02 Jun 2022
Accepted: 29 Jul 2022
e-Available: 09 Aug 2022

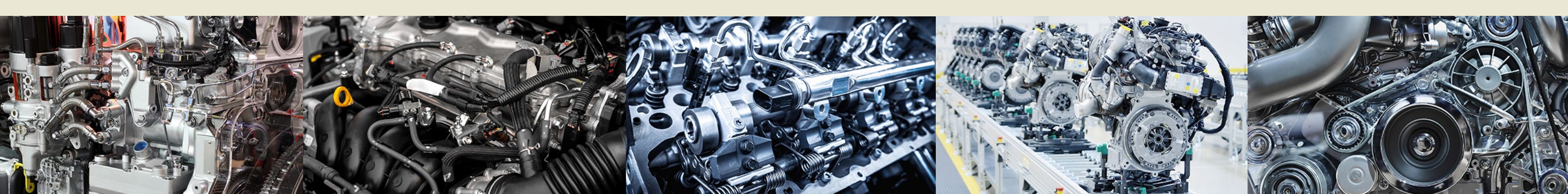
Keywords

Intelligent health management, Prognostics, Driving behavior, Machine learning, Diesel particulate filter

Citation

Doikin, A., Campean, F., Priest, M., Angiolini, E. et al., "Driving Behavior Modelling Framework for Intelligent Powertrain Health Management," *SAE Int. J. Engines* 16(4):2023, doi:10.4271/03-16-04-0026.

ISSN: 1946-3936
e-ISSN: 1946-3944



1. Introduction

The automotive market has seen significant transformations over the past 50 years, substantially influenced by fast technology developments in electronics, software, and networks. From a powertrain perspective, growing system complexity introduces new challenges. The vehicle is made up of several thousand physical parts/components, which interact dynamically in diverse conditions to deliver the functional requirements of the system. An unexpected breakdown can affect customer satisfaction and undermine the credibility of the automaker. According to Holland [1], quality and reliability account for 38-41% of the overall vehicle customer satisfaction; therefore, a sharper focus on integrated vehicle health management (IVHM) is needed to enhance dependability to meet the growing customer expectations.

The IVHM approach is the current state of the art in the field of health management in complex systems [3]. The IVHM concept was originally developed by the aerospace industry with significant contributions from NASA and Boeing [4]; however, later application was found in other sectors, including energy [5], maritime [6], manufacturing [7], and automotive [8]. Although IVHM is an integrated approach, where the vehicle is considered as a whole [3, 9], it still requires robust health assessment on lower system levels, including components. The recently introduced aerospace and automotive recommended practice JA6268 [10] is targeted at components and subsystems, which have been augmented to monitor and report their own health, enabling further integration into vehicle- or platform-level application.

In practical terms, this can be achieved through enhanced system diagnostics and prognostics. The recent proliferation of sensors connected through the Internet of Things (IoT) increases vehicle interconnectivity with the environment and offers new opportunities in the field of health management. On the other hand, this growing volume of collected data is currently not utilized efficiently: the automotive industry spends 50 billion euros every year to collect and save such data which are not used later [2]. The potential of real-time monitoring data is currently not fully exploited for health management as it is often limited to diagnostics for offline intervention (as maintenance/repairs), with limited online proactive health management actions. Increasingly, the vision for IVHM seeks to optimize the performance of the system and maintain optimal levels of performance in operation, and not only to predict and mitigate actual faults and failures. This approach is underpinned by online data-driven diagnostics and prognostics modelling, which has become a very active area of research.

While good progress has been made with the development of online diagnostics for automotive propulsion systems and components, in particular for emissions compliance monitoring and more recently for battery electric vehicles state of health monitoring, methodologies and examples for advanced prognostics and intelligent health management of propulsion systems are limited. The objective of the research underpinning this article is to address this gap by proposing a comprehensive framework for intelligent IVHM strategies.

A main challenge with robust prognostic modelling of propulsion systems is the limited predictive insight on future operating conditions. The automotive field is more difficult in this respect compared to many other industries as future usage depends not only on duty cycles but also on driver behavior patterns. The approach introduced in this article centers on a classification machine learning (ML) approach for driving behavior modelling, covering both duty cycles and driver behavior, based on data collected from car journeys. The predictive insight derived from the ML models is then used for short-term prognostics based on the current state of the system (diagnostics) and progression expected within the next journey or series of journeys. This supports the development and implementation of optimal IVHM strategies based on intelligent propulsion systems control strategies.

To provide a comprehensive illustration for our proposed approach, we consider the case study of an emissions aftertreatment system—the diesel particulate filter (DPF). We introduce a reliability state-based paradigm to model the operation of the DPF, with the active regeneration event construed as health management intervention. A revised DPF control strategy is proposed, underpinned by predictions from the driving behavior ML model, trained and validated with a large data set of real-world driving. The validation of the proposed intelligent DPF control strategy is based on an industry standard model-in-the-loop simulation.

The article is structured as follows: Section 2 provides a comprehensive review of related work on diagnostics and prognostics; Section 3 introduces the proposed methodology for driving behavior modelling; Section 4 introduces the DPF case study, and the proposed intelligent DPF control strategy based on the reliability states-based model with ML predictive driving behavior input; Section 5 presents the results and analysis of the ML driver behavior modelling and performance evaluation for the proposed intelligent DPF health management strategy, followed by a discussion and conclusions.

2. Review of Related Literature

2.1. Diagnostics and Prognostics Challenges

Integrated vehicle/system health management (IVHM/ISHM) framework became an application of open system architecture for condition-based maintenance [11, 12] in a more complex system of systems engineering [13, 14]. Although IVHM is described as an integrated approach, where the vehicle is considered as a whole [3], it still requires robust health assessment at a component/subsystem level to feed the integrated vehicle- or platform-level applications, as suggested in the SAE JA6268 standard [10]. The main IVHM development steps have been discussed by Larsen et al. [15], emphasizing the implementation reliance on real-time diagnostics and prognostics. Diagnostics is associated with the current health state estimation, while prognostics extends to the evaluation of the remaining useful life (RUL) [16]. In modelling terms, health state is usually expressed as a measure of the accumulated damage [17], where 0 indicates the best health condition and 1 stands for a failure threshold (worst health condition).

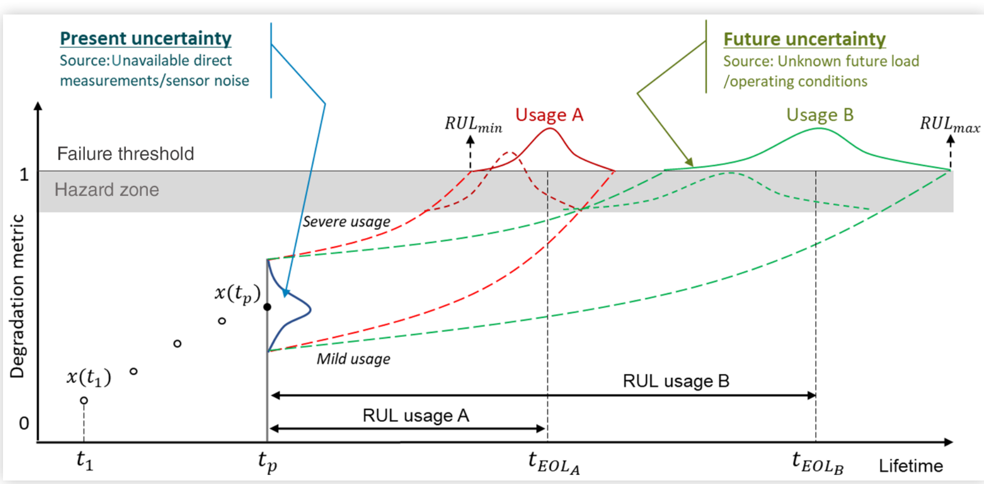
In general, diagnostics is a more mature field in comparison to prognostics, which remains a challenging area of study. However, since prognostics also rely on diagnostics output [18], challenges of both can be discussed within an uncertainty context, as illustrated in Figure 1. Uncertainties affect the robustness of RUL estimation, but it is important to understand that they always exist as they are an integral part of the modelling process. Sources of uncertainties arise from various factors and have been widely discussed in the literature [19, 20, 21, 22], including inaccuracies in measurements and sensor noise, manufacturing variations, operating environment, unknown future operating load, material properties, piece-to-piece variation, etc. In general, sources of uncertainties can be classified into aleatoric (arise from inherent variability) and epistemic (arise due to lack of knowledge) [23, 24]. Sankararaman [25] discussed uncertainty sources from a degradation modelling perspective and combined them into four main categories:

- Present uncertainty—related to the precise estimation of the component/system current health state based on the direct damage measurements or estimation using filtering techniques.
- Future uncertainty—probably one of the most significant sources of uncertainty coming from unknown future operations, including loading and environmental conditions.
- Model uncertainty—relates to the uncertainty associated with model parameters, both current and future; if model parameters have a bias or are not accurate (underfitting or overfitting), then there will be discrepancies between the model predictions and actual RUL.
- Modelling method uncertainty—describes the combined effect of all uncertainties together. Even with the assumption of all the above uncertainties can be precisely calculated, their combined effect needs investigation. This creates additional uncertainty as precisely deriving the overall uncertainty effect is a significant challenge.

The source of present uncertainty is more significant when damage cannot be inferred directly, which is a common challenge in engineering applications. In an approach to overcome this, indirect sensor measurements of other physical properties around the system are correlated with the accumulated damage [15, 26, 27]. As an example, a prototype for oil pump diagnostics was proposed based on available sensor data across the engine, considering a model-based hierarchical system decomposition [28]. However, even if direct measurements are available, the robustness of the current health state estimation is still affected by sensor fidelity [22], where measurement noise can be caused by electrical interference, digitization error, sensor bias, dead-band, backlash, and nonlinearity in the response [19].

Prognostics modelling capabilities are often limited by unknown future operational conditions, which are described in the literature as the most significant source/factor of uncertainty. In terms of life modelling, they result in future uncertainty, which represents failure time in probabilistic terms. As a result, many of the existing approaches are limited by steady-state conditions. For example, Eker et al. [29] integrated physics-based model with Particle Filter to predict future filter clogging levels. Rebello et al. [30] applied Dynamic Bayesian Network for chemical plant reliability modelling. Cheng et al. [31] combined Support Vector Machine (SVM) with particle filter for proton exchange

FIGURE 1 Uncertainty quantification in prognostics modelling.



membrane fuel cell RUL computation. However, automotive operating conditions are subjected to much more transients, which vary from duty cycles as well as depend on individual driver behavior habits. Altogether, this makes future vehicle operating conditions much more uncertain and produces further modelling challenges. The work presented in this article makes the argument that uncertainty around failure time may be significantly reduced through driver behavior modelling. In the reviewed literature, driver behavior modelling is mostly focused on driver identification. For example, Marchegiani and Posner [32] applied SVM for driver behavior modelling based on the rate of acceleration and braking. Wang and Ho [33] used Deep Neural Network modelling for specific driver identification based on maneuver classification. In this research, the problem is analyzed from a different angle and assumes that future operating conditions may be abstracted from accurately classified trip types. Therefore, the next section contains a review of data-driven approaches, which may be considered for the driver behavior modelling challenge.

2.2. Data-Driven Modelling Approaches

Data-driven modelling can be implemented with statistical (or empirical based) and ML approaches. Statistical (or empirical based) methods attempt to fit the empirical model as close as possible to the collected data to characterize the degradation process, ignoring any physics principles [27]. To do so, no training and testing data sets are required as the model is evaluated based on the significance and robustness of model parameters. Although such models can be used to make predictions, the main purpose is characterizing the relationship between variables, known as statistical inference [34]. Uncertainties caused by temporal variability, unit-to-unit variability, nonlinear variability, and measurement variability are represented using model parameters, which can be later updated using condition monitoring data [35]. Commonly, according to observations from measurements, the RUL prediction result is illustrated as a conditional probability density function (pdf) [36].

In contrast to statistical models, ML models prioritize prediction accuracy over interpretability and can be unsupervised and supervised. Unsupervised techniques are designed for unlabelled data sets to learn and identify patterns, where clustering [37], pattern recognition [38], and principal component analysis [39] are the most commonly used methods. Supervised learning uses labelled data sets to train algorithms and can be used for classification and regression problems. The first is aiming to predict a label class while the second is about predicting the actual quantity. The key and the most common supervised training approaches are described below; however, a more detailed review can be found in Si et al. [36], Ye and Xie [40], and Lei et al. [41], who also described autoregressive models, random coefficient models, Wiener process models, gamma process models, inverse Gaussian process models, Markov models, and proportional hazard models.

A decision tree is a supervised learning algorithm mainly used for classification purposes [42]. During the training, data are continuously split according to defined parameters [43] to represent the predictive model with a tree, which consists of nodes (attributes in a group that is to be classified) and branches (values that a node can take) [44]. The power of a decision tree model is the ability to break down effectively a complicated decision-making process into a set of simpler decisions, providing a white-box model solution for easier interpretation [45]. Some other advantages include relatively low computational cost, resilience to incomplete/missing data, and the ability to be combined with other decision models [46, 47]. However, their application may be limited by known challenges including instability, poor performance with imbalanced data, and relatively low accuracy in comparison to other methods.

Linear discriminant analysis is another supervised training method, which separates classes of objects using a linear combination of features. It assumes that predictors follow the mixture of Gaussian distributions [48], and covariance in each class is the same [49]. The main challenge comes if classes are nonlinearly separable, and data has a small sample size [50]. However, the sample size problem can be partially compensated with data regularization [51], subspace method [52], or null space approach [53]. Hard model interpretation and sensitivity to noise are other drawbacks of discriminant analysis [54].

The Naïve Bayes is a probabilistic classifier technique, which is more efficient with high-dimensional data sets [55]. This model is widely used due to its simplicity and can also be easily updated with new data on the go. The main advantages are low requirements in training data sample size and low computational load [56]. However, the assumption of independent predictors, which is almost impossible to satisfy in real-world applications, is the main drawback of Naïve Bayes [57]. Various techniques were developed to overcome this limitation [58]. Another significant disadvantage is that this model is unable to make predictions on new observations, which were not in the training data set.

The SVM learning technique works on the principle of margin calculation, aiming to maximize the distance between the margin and the classes [42]. Its popularity comes with versatility, making it suitable for a wide range of problems. The technique has a lower risk of overfitting, is efficient with nonlinear data, and works well with small sample sizes. Nevertheless, for nonlinear applications, this model is very sensitive to hyperparameters, and their inaccurate choice can affect performance [59]. SVMs are criticized for computational intensity and memory requirements. Like many other approaches, SVMs are treated as black boxes, which are hard to interpret.

The K-nearest neighbors (k-NN) algorithm is a nonparametric classification algorithm. It stores all training data and assigns a new observation to the class of the nearest set of previously labelled points [60]. Euclidean distance is the most common and efficient measure to compute the distance, although other measures are also available [61]. The method is good for multimodal classes and data sets with joint distributions. Performance is susceptible to selecting the most suitable value of "k" and varies according to the data sample size. Overall, k-NN has lower computational efficiency due to the lazy learning approach [49].

Ensemble learning is a combination of individual learners to enhance overall performance [62]. Sagi and Rokach [63] have reviewed and compared various ensemble learning methods, including AdaBoost, bagging, random forest, random subspace methods, gradient boosting machines, error-correcting output codes, rotation forest, extremely randomized trees, and stacking. Out of all methods, boosting approach attracts particular attention due to its efficiency with highly imbalanced data [64]. This is achieved through the conversion of multiple weak learners into a single composite robust classifier [65]. Moreover, boosting is also a reliable method that easily avoids model overfitting. RUSBoost is treated as the most powerful algorithm in its class, which is built on SMOTEBoost [66] and AdaBoost [67] algorithm principles, but reports improved performance and lower computational load along with overall simplicity.

Artificial neural networks (ANNs) are computing systems based on the neuronal structure, where the processing method received inspiration from biological neural networks [68]. The technique has an advantage over some conventional methods, which are limited by strong assumptions of normality, linearity, variable independence, etc. [49]. ANNs can capture complex relationships in nonlinear and dynamic problems; however, its interpretation is almost impossible. They are also more robust in relation to incomplete/missing data. A complete structure of a conventional ANN includes at least three different layers: the input, the hidden, and the output [69], where each layer consists of a certain number of neurons interconnected with all the neurons in the next layer [70]. The challenge is to determine the size of the hidden layer as underestimation can result in poor accuracy, whereas overestimation is likely to cause overfitting [49].

The methods discussed so far belong to the shallow learning family. The term "deep learning" is used for a branch of ML algorithms with a higher level of complexity. The backbone is represented by neural networks, which normally have a much higher number and larger size of hidden layers in comparison to shallow ones. The main deep learning-based techniques are Deep Convolutional Neural Network, Deep Recurrent Neural Network, Restricted Boltzmann Machine-Based Deep Neural Network, and Autoencoder-Based Deep Neural Network [71]. In general, deep learning requires less data preprocessing and is able to extract features of interest (missed by domain experts) automatically [72]. Deep learning provides a significant advantage and outperforms shallow learning techniques when larger amounts of data are available [73]. However, this comes at a cost of computational intensity compared to other methods [74, 75].

In practical terms, there is no immediate conclusion on which algorithm is expected to be the most suitable for a driver behavior problem. However, the development of predictive models for practical automotive applications should consider electronic control unit (ECU) computational power and memory limitations [76], which create limitations for deep learning approaches. On the other hand, hardly interpretable black-box approaches may be hard to accept by the industry for real-world deployment. In such realities, decision trees, which work as a white-box model solution, have relatively low computational cost, are resilient to incomplete/missing data, and are able to be combined with other decision models [46, 47], can be an attractive modelling method for an industrial application.

3. Proposed Methodology for Driver Behavior Modelling for Health Management Applications

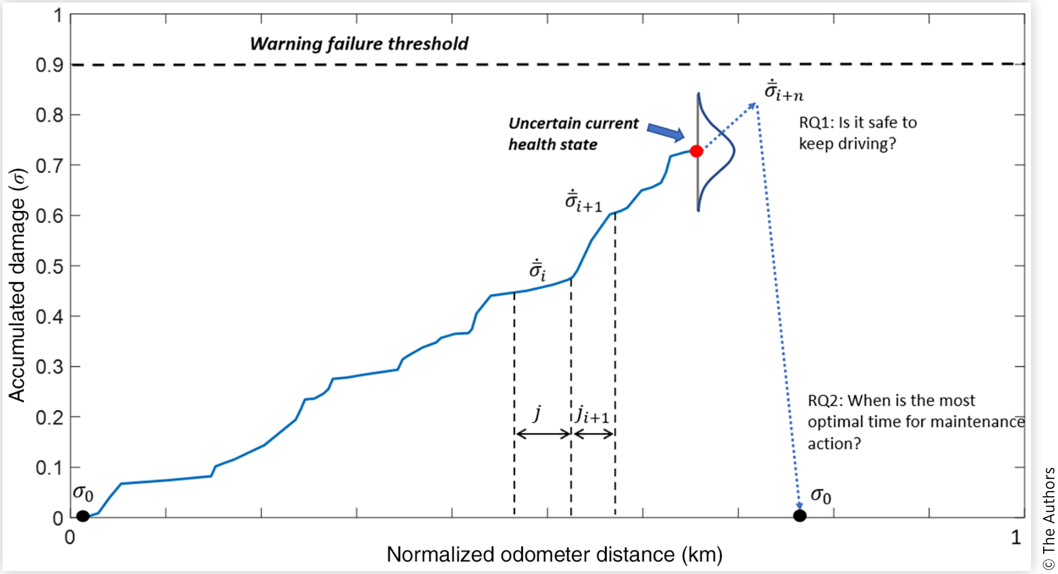
From a reliability perspective, the interest in driver behavior modelling is to predict upcoming vehicle usage in order to anticipate the progression of damage accumulation, evaluate RUL, and support proactive repair action decisions and planning. In practical terms, this helps to understand how many journeys (or kilometers) a vehicle can do until repair action is required, as a basis for optimizing the powertrain availability, durability, and overall operational costs. Therefore, the damage accumulation σ process can be discretized in relation to journeys j as illustrated in Equation 1.

$$\sigma = \sigma_0 + \sum_i \overline{\dot{\sigma}_i} \cdot j_i \qquad \text{Eq. (1)}$$

where σ_0 denotes the initial damage at the start of the operational cycle (i.e., new or after a repair action), $\overline{\dot{\sigma}_i}$ defines the average damage accumulation rate for the journey index i, and j_i represents time-series metric (such as distance, time, etc.) of the journey i. Given that journey types can be different in terms of damage severity, modelling future usage can significantly increase confidence in RUL estimation. Figure 2 provides visualization for the damage accumulation prediction problem for an intelligent health management context. The current health state estimation is uncertain due to sensing uncertainty and/or cumulative errors in model-based estimation approaches. This uncertainty feeds into the RUL prediction modelling, which needs to evaluate the safety of completing future journeys without reaching a critical failure threshold or state. Mitigating actions for health management includes not only maintenance interventions but also active powertrain control strategies for self-healing. Therefore, prognostics is important for optimizing online powertrain control strategies.

The proliferation of IoT technologies in vehicle and powertrain applications supplies a growing amount of real-world driving data from real-time vehicle communications (such as Data over the Air) to be used for gaining a better

FIGURE 2 The role of driver behavior modelling in damage accumulation problems.



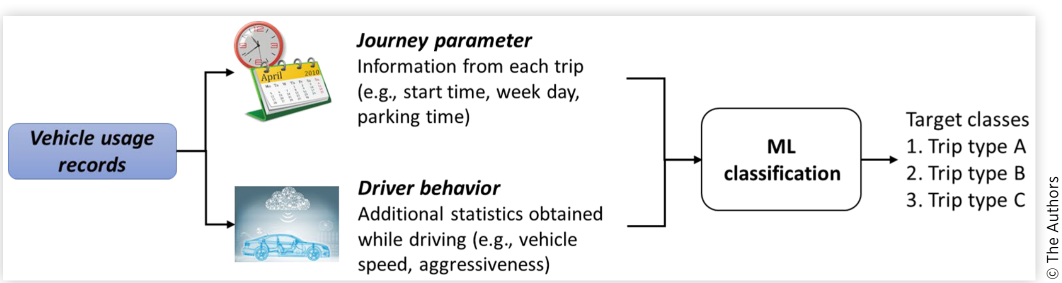
understanding of vehicle usage patterns and drive cycles in order to enhance control strategies for personalized powertrain health management and a better user experience.

In this research, the proposed driver behavior modelling methodology is underpinned by historical vehicle trips to learn the usage pattern and come up with a predictive model, which is suitable for real-time predictions. While in the reviewed literature, driver behavior modelling is mostly focused on driver identification, in this research the problem is analyzed from a different angle and hypothesizes that future operating conditions may be abstracted from the classification of historic journey types and observed behaviors. Figure 3 provides an illustration of the proposed approach. The information from vehicle usage records of historical trips for a particular vehicle can be classified into journey parameters (generic records from each trip) and driver behavior characteristics collected during the journey (such as a measure of aggressiveness and average speed). At one level, modelling can be purely based on journey parameters; however, driver behavior characteristics provide essential additional information to improve the predictability of damage accumulation and feasibility of active health management interventions.

As discussed in the critical review of literature on data-driven models (Section 2.2), there is no immediate answer on which classification algorithm is the most suitable. In general, decision trees can be attractive and perform as a white-box model, and have a relatively low computational cost. On the other hand, boosting techniques can outperform with imbalanced data sets. Therefore, for the purpose of this study, we considered to test the main ML algorithm families with demonstrated merit in a wide range of similar problems, including Decision Trees, Logistic Regression, Linear Discriminant Analysis, SVM, k-NN Classifier, and Neural Networks.

Although computational requirements depend on the choice of algorithm for model training, it is worth mentioning that using averaged trip summary also aims to reduce the load for real-time automotive ECU calculations. Therefore, the outlined concept is designed to be suitable for real-world applications. On the other hand, assuming that data can be sent over the air, training can be performed on a remote server, which can be an alternative solution. In both cases, models can be periodically updated (the frequency of such updates comes from the requirements defined by the field of application) and kept up to date once new usage records are available.

FIGURE 3 Proposed driver behavior classification modelling concept.



4. Case Study

4.1. DPF Background

Using a DPF in an aftertreatment system is an efficient way to meet the latest vehicle emission legislations, which are becoming stringent every year. Ceramic wall-flow monoliths remain to be the most common solution for removing particulate matter (known as soot particles) from the exhaust flow, produced as a result of fuel combustion. Figure 4 illustrates real-world usage cycles where the mass of trapped particles, annotated by pattern (i), is proportional to the backpressure increase in the exhaust system, which negatively affects the engine operation [77]. The soot mass can also decrease (ii) if the exhaust gas temperatures are high enough to cause a passive regeneration (also referred to as "spontaneous") [78]. In addition, the filter requires periodical active regeneration [79], which is triggered by raising the exhaust gas temperature using fuel post-injection to burn particulates and restore the filter (iii). The triggering decision is based on a soot mass value, indicating the filter is close to the critical load. Failure to deliver this function on time may result in a soot overloading failure mode [80] triggering limp mode activation, as any further attempts to regenerate can damage the catalyst as well as the other systems [81].

However, a successful regeneration requires around 10-15 minutes of driving under certain conditions to ensure that a sufficient mass flow of gas at the required temperature is passed over the DPF. If the journey is not long enough, this causes an interrupted regeneration process (iv), reflecting on the overall cost function of the regeneration process [82]. In simple terms, the cost of regeneration (C) can be defined as

$$C = C_{wp} + C_{reg} \qquad \text{Eq. (2)}$$

where C_{wp} defines the cost of DPF warm-up (reach target temperature to initiate soot burning) and C_{reg} is the cost of regeneration itself (maintaining temperature to allow soot burning). Given that the system may have multiple attempts to regenerate, and the cost is associated with the amount of fuel injected, the cost of regeneration C_{RPC} per cycle can be written as

$$C_{RPC} = \sum_{i=1}^{k} \left(\overline{\dot{FC}}_{wp_i} \times d_{wp_i} + \overline{\dot{FC}}_{reg_i} \times d_{reg_i} \right) \qquad \text{Eq. (3)}$$

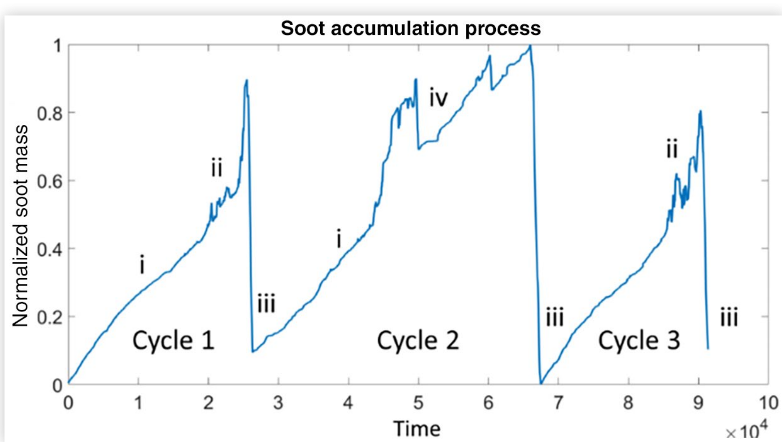
where k is the number of attempted regens, i represents the journey index, $\overline{\dot{FC}}_{wp}$ is the average fuel consumption during the warm-up state, $\overline{\dot{FC}}_{reg}$ is the average fuel consumption during the regeneration state, and d_{wp} and d_{reg} stand for the duration of warm-up and regeneration, respectively. Strictly speaking, the mathematical formulation can be simplified to the fact that interrupted regenerations decrease fuel efficiency and, therefore, such events should be minimized where possible. The argument taken in this work is that data-driven techniques for driver behavior modelling can be used to provide predictive insight for control strategy enhancement and optimization.

4.2. Problem Statement

The literature defines two strategies for active regeneration: time based and threshold based [83]. The first strategy is based on elapsed engine operating hours, which can be varied depending on the usage profile. The control strategy considered in this study is based on the second approach, which is based on a predefined soot mass threshold limit. In the context of powertrain health management, the amount of accumulated soot, known as particulate matter, is associated with the current health state of the DPF. Soot mass is commonly inferred from a combination of sensing (using fitted measurement equipment) and model-based approach (underpinned by mathematical modelling).

The differential pressure sensor monitors the exhaust gas flow backpressure increase across the DPF, which is correlated with the amount of soot. However, it may lack accuracy in the case of insufficient mass flow rate. In addition, uncertainties

FIGURE 4 Real-world soot accumulation process.



also arise from the size of particulates, which can have a significant impact on the pressure drop [84]. Recent studies report the overall onboard diagnostics index error around ±28%, which is expected to be higher at excessive transients [85].

The model-based approach is based on modelling of the combustion process with the attempt to account for the in-cylinder soot formation factors—both static (e.g., combustion chamber design, air induction, and fuel injection design parameters) and dynamic parameters (either global engine parameters, like engine speed and torque demand, or state-based combustion control parameters, the fuel chemistry, as well as the combustion thermodynamics and reaction kinetics, post-combustion factors) [86]. It also includes the modelling of the processes in the exhaust aftertreatment systems to account for the soot regeneration processes—both passive and active [87]. Thus, the model-based approach is affected by uncertainty in other sensors and also the modelling method uncertainty, which is based on stored models—embedding modelling uncertainty—and assumptions about the dynamic stochastic behavior. The modelling errors are more significant during transient states, which is the main drawback of the model-based approach.

From a reliability perspective, the soot accumulation process in the DPF can be regarded as a "damage accumulation" process by adapting Equation 1:

$$m = m_0 + \sum_i \overline{\dot{m}_i} \cdot d_i \qquad \text{Eq. (4)}$$

where m is the current soot load (in grams) in the DPF, m_0 is the soot mass at the beginning of the cycle (initial soot mass), $\dot{m}_i$ is the average soot rate for the journey i, and d_i is the duration of the journey i. The system is repairable through thermal regeneration; however, the success of operation depends on the journey type. The current DPF health management is based directly on diagnostics, which is about predicting the current soot loading m. In operational terms, it means that maintenance action (i.e., regeneration) is needed once the predefined threshold is reached. However, since both estimation approaches (sensor and physics based) are affected by uncertainties, the soot mass threshold for active regeneration triggering is lowered for safety reasons to avoid potential soot overloading failure mode. Moreover, inaccuracies in estimations can cause "underloading", resulting in unnecessary DPF regenerations [78]. Therefore, research efforts are targeted to deliver further system optimization. For example, in a recent study, Barba et al. [88] presented a methodology focusing on a more reliable engine-out soot mass simulation approach. Dawei et al. [89] proposed a new method for DPF regeneration, underpinned by a mathematical model for more accurate regeneration timing and temperature control. Castellano et al. [90] introduced a novel adaptive control strategy for temperature control using fuel post-injection, which reports an improvement in regeneration quality. Hopka et al. [91] used Global Positioning System (GPS) route destination information for smart DPF regenerations. However, all the reviewed research work also revolves around diagnostics, while benefits associated with prognostics modelling are not fully revealed.

From a control strategy viewpoint, prognostics is associated with predicting possible future system scenarios, as illustrated in Figure 5. This becomes especially relevant once soot mass (whose accuracy is uncertain as discussed before) reaches a predefined threshold and regeneration is requested. The success of the maintenance process to restore DPF loading

FIGURE 5 Driver behavior uncertainties within the DPF soot accumulation process.

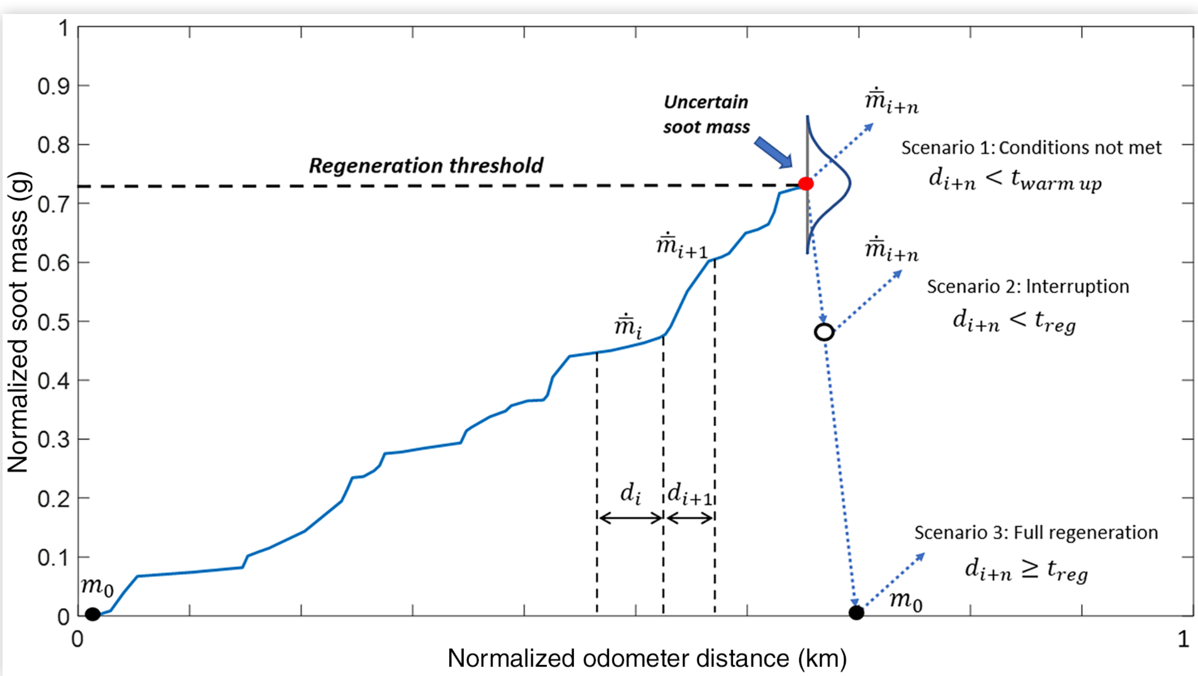
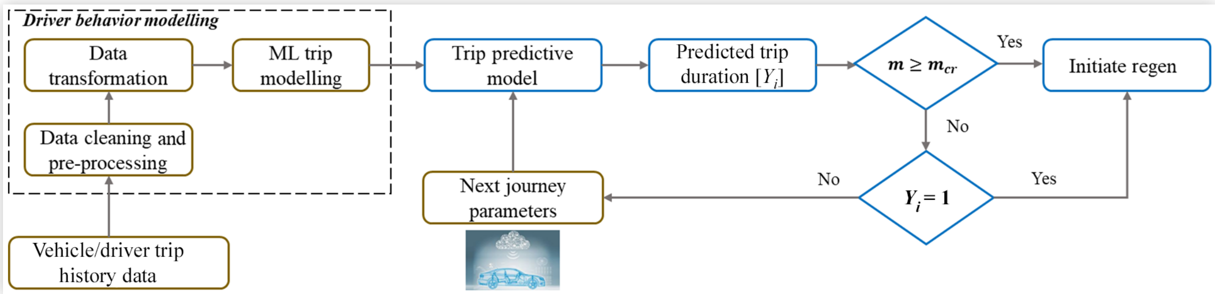


FIGURE 6 Proposed data-driven modelling for DPF health management optimization.



depends on the type of the journey, which, in simple terms, from a user perspective, can be associated with the journey duration that needs to be long enough to allow complete soot burning. Shorter journeys can cause further soot growth in case regeneration is not triggered, which happens if the journey duration is not long enough to meet suitable conditions $d_{i+n} < t_{warm\ up}$. The partial soot burning occurs if the regeneration process is triggered but the journey duration does not allow to complete the process of burning completely $d_{i+n} < t_{reg}$, resulting in process interruption. These occasions are illustrated as possible Regeneration scenarios 1 and 2. To maximize the system efficiency, Scenario 2 should be replaced with Scenario 3 (full regeneration) wherever possible. However, future operating conditions are fully uncertain, which leads to interrupted regenerations. According to the real-world DPF usage data, on average approximately four attempts are required in each accumulation cycle until the complete DPF regeneration occurs.

This study introduces an intelligent DPF control strategy to reduce carbon dioxide (CO_2) and operational costs and enhance reliability. In our previous work [92], a knowledge-enabled framework was introduced to improve system state predictability and avoid early regenerations caused by diagnostics inaccuracies in current soot load estimation. This study extends the previous to driver behavior modelling in order to predict the type of upcoming trip and choose an optimal journey, which satisfies the duration requirements for a successful/complete DPF regeneration. Figure 6 summarizes the generic method to predict expected vehicle usage with a data-driven modelling approach. First, data is subjected to cleaning, preprocessing, and transformation depending on the use case scenario and also the requirements for the ML training algorithms. The vehicle trip history database is regularly updated with new usage records, maintaining the data-driven model up to date depending on the current usage profile. The model itself aims to predict the type of the upcoming journey and, hence, abstract future operating conditions, which are then fed into a decision block.

4.3. Intelligent DPF Health Management

The philosophy of intelligent regeneration strategy underpinned by driver behavior modelling assumes to attempt a regeneration only when a long enough journey is predicted. In the context of data-driven modelling, this simplifies the challenge of thebinary classification problem, as shown in Equation 5:

$$Y_i' = \begin{cases} 0, if\ Y_i < X_{cr}\ minutes \\ 1, if\ Y_i \geq X_{cr}\ minutes \end{cases} \qquad \text{Eq. (5)}$$

where 0 stands for short journeys, 1 represents journeys capable to deliver successful regeneration, and X_{cr} is a critical value defining the time required to complete the DPF repair process. Although X_{cr} can be approximated, the actual regeneration duration is not fixed and may vary approximately between 10 and 20 minutes, depending on the duty cycle. This is illustrated in Figure 7, noting differences between different regeneration cycles in trip duration requirements, which were normalized for confidentiality reasons. In practical terms, the expected regeneration duration is known from input parameters at the start of regeneration (such as emission temperature and current driving conditions). Therefore, this challenge can be addressed by using multiple driver models with different duration thresholds to cover the whole spectrum of regeneration cycles. However, for the sake of concept demonstration and simplicity, this assumes that duration is fixed in all cases and uses X_{cr} threshold to cover a vast majority of cycles.

However, a sequence of short trips with postponed regenerations can incur the risk of reaching a critical soot load state. To ensure system reliability and avoid potential soot overloading problem, an additional safety layer is added to the control strategy, illustrated as a DPF warning load (State 4) in Figure 8.

The primary aim of State 4 is to control the soot limits when the system allows reference to the driver behavior model. Figure 9 explains the flow of logic for the proposed intelligent DPF health management strategy. Soot mass is regularly updated and keeps accumulating while the DPF is in State 1 or State 2. Regeneration is requested in State 3, where an algorithm refers to a trip prediction model to find a suitable journey based on the duration criteria and burn the soot. In the case of successful regeneration, the DPF returns to State 1, and a new soot accumulation cycle begins. However, if the DPF has reached State 4, regeneration is attempted despite the model prediction, assuming that partial regeneration is better than State 5 with a forced regeneration requirement.

FIGURE 7 Normalized duration for DPF regeneration cycles.

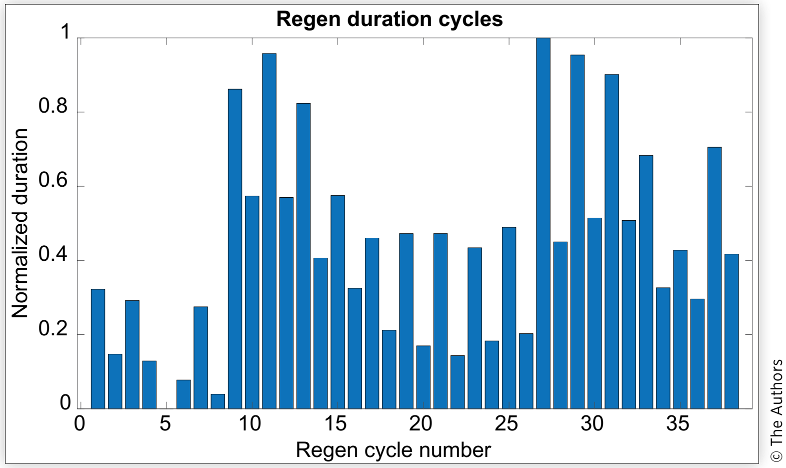


FIGURE 8 DPF state-based control.

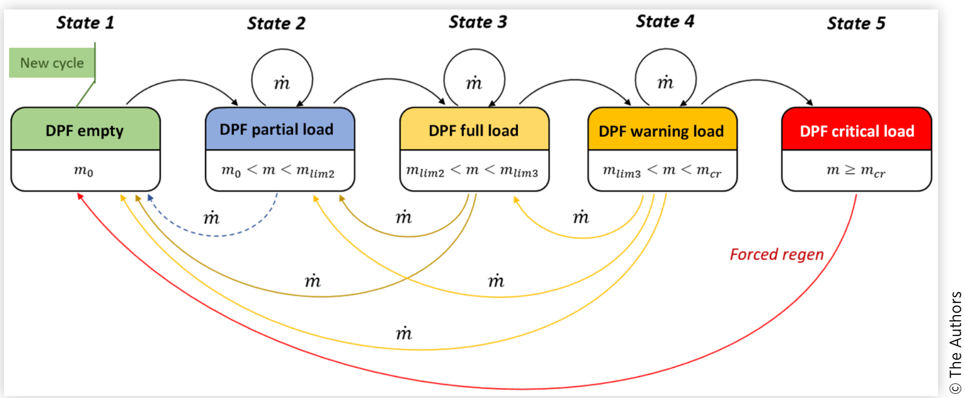
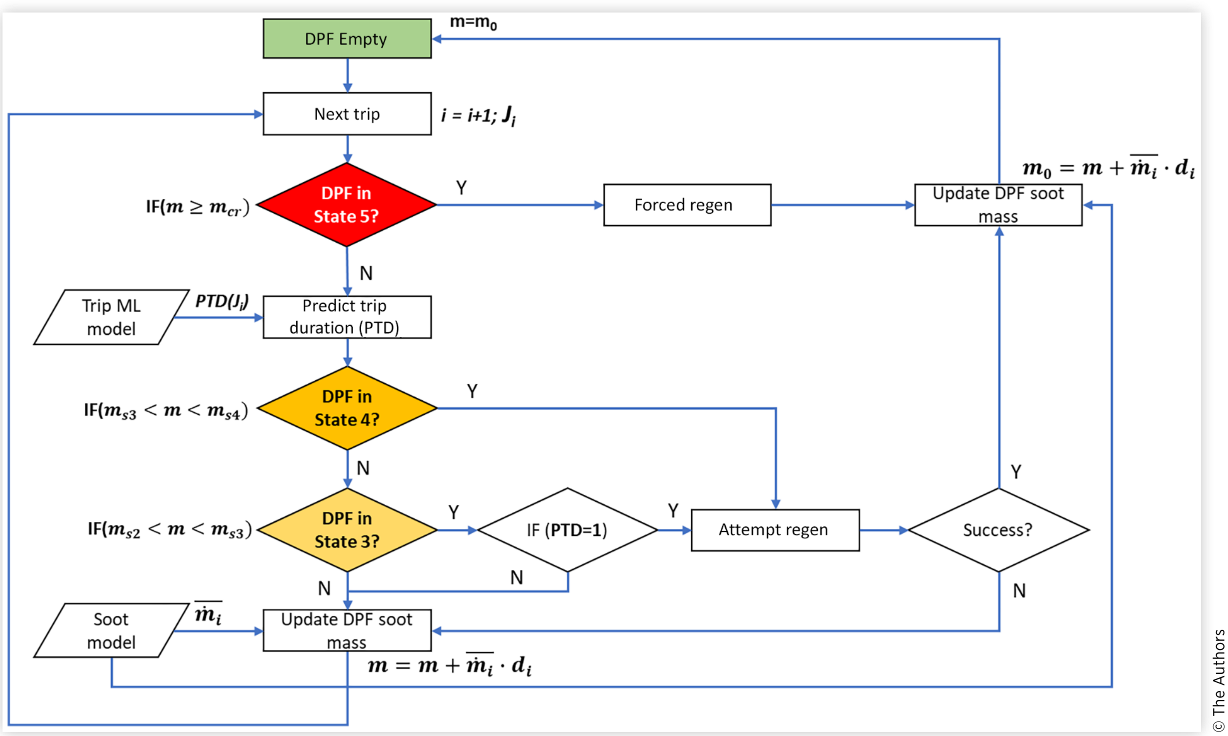


FIGURE 9 Proposed intelligent DPF health management framework.



The proposed health management strategy is expected to reduce the number of interrupted regenerations against the current strategy, where regenerations are always attempted once State 3 is reached. In the next section, method efficiency is validated via the simulation of a real-world data.

5. Results and Analysis

5.1. ML for Driver Behavior Modelling

A sample of historical real-world driving journeys, collected as data over the air was available for this study. The data covered journeys of 100 individual vehicles (family-type passenger cars, such as sedans and crossovers) over a period of 3 to 4 months of driving, including the history of journeys as a statistical summary for each trip. Each record in the data set described a journey from point A to point B, as illustrated in Figure 10. This included higher-level journey parameters (such as journey time stamp, which can be used to extract the day of the week and calculate duration), and also driver behavior features. Driver behavior features included a set of parameters, which depend on the way the car is driven (including, e.g., the averaged fuel consumption and metrics of driver aggressiveness). Given that triggering regeneration requires meeting certain driving conditions, driving statistics from the first minutes of the journey (i.e., before regeneration decision is made) can be used to enhance journey predictability. The sample size was variable with regard to the number of recorded journeys in the observation period and contained an average history of 500 to 700 trips per vehicle.

The data preparation for the ML process flow included several steps. First, data were subjected to cleaning and preprocessing to satisfy data quality requirements This included identification of missing values, as well as outliers—as values outside the expected range. Such removal was based on engineering judgment, e.g., deleting negative values for the duration or abnormally high spikes due to sampling error. In the next step, the binary transformation was applied for the variable of interest from a prediction point of view (i.e., journey duration), based on Equation 3. However, since customers tend to run short journeys more frequently, the applied binary transformation is causing data imbalance for some of the vehicles, which is known to cause difficulties for ML training algorithms. Moreover, standard accuracy measures to evaluate algorithm performance may be inefficient here as it is biased toward the majority class [93]. Normally, F_β is applied as a better measure of accuracy [94]; however, it has limitations when comparing models with different rates of imbalance. Since there are 100 separate models (and the rate of imbalance for each vehicle is different, which can also be for both classes since there are 100 separate models), F_β is also not an efficient measure to allow fair comparison between vehicles. Therefore, classification accuracy has been inferred by taking the average between the rate of true positives over false negatives and the rate of true negatives over false positives, also known as balanced accuracy [95]:

$$\text{Accuracy measure} = \frac{\text{TP} + \text{FP}}{2} \qquad \text{Eq. (6)}$$

where true positives (TP) and false positives (FP) represent model prediction confusion matrix components. Figure 11 illustrates the model validation confusion matrix for a

FIGURE 11 Confusion matrix.

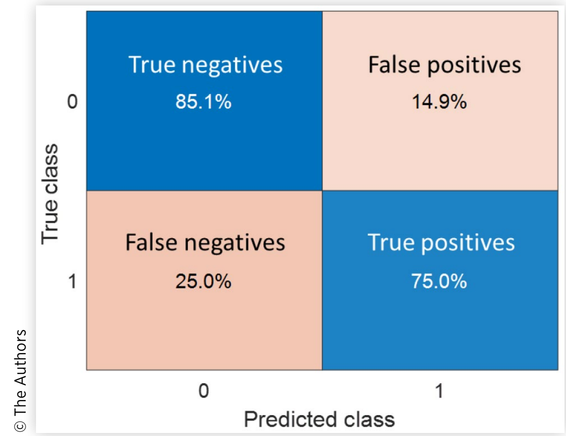


FIGURE 10 Setting up a data-driven model.

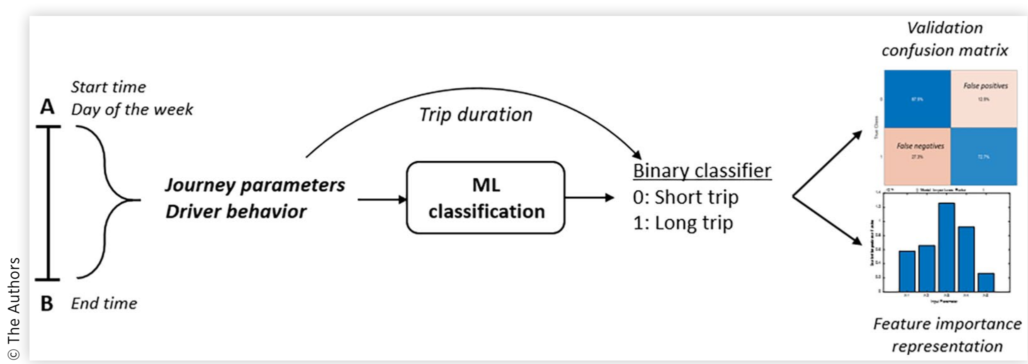


TABLE 1 Average performance evaluation for ML algorithms on unseen data.

Algorithm tested	Balanced accuracy (%)	TP accuracy (%)	TN accuracy (%)
Decision Tree	68	66	70
Logistic Regression	60.5	55	66
Linear Discriminant Analysis	66	57	75
Support Vector Machine	64.5	53	76
k-NN Classifier	61.5	60	63
Neural Network	68	65	71
RUSBoosted Tree Ensemble	**73**	71	75

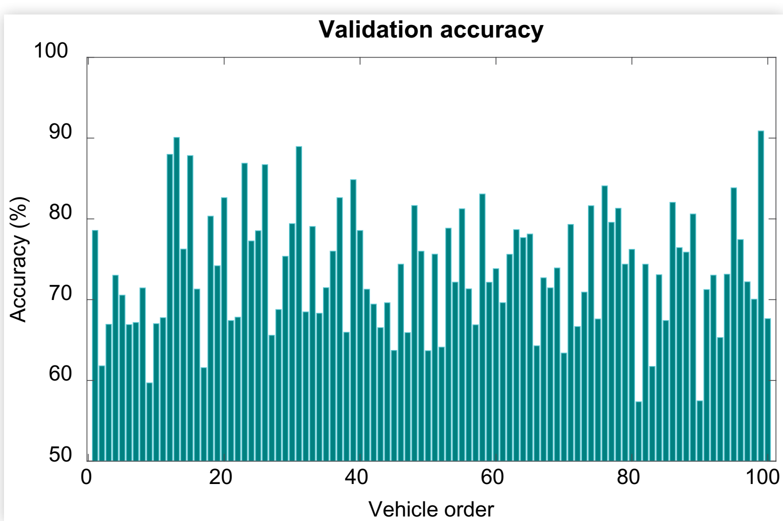
classification ML model (Decision Tree in this case) for a randomly selected vehicle. It is important to note that from the regeneration optimization viewpoint, the priority is to reduce the rate of false positives, which, in the first instance, leads to interrupted regenerations. On the other hand, false negatives are also undesirable, but such cases are treated as a missed opportunity to regenerate, while the primary aim is to minimize interruptions.

Table 1 presents the average trip modelling classification accuracy results from 100 vehicles across tested ML modelling algorithms considered for this study, as discussed in Section 3. In all cases, 75% of data was used for model fitting and the remaining 25% was left for testing on unseen data. The number of data rows for training (where each row corresponds to one trip) ranged from 300 to 550 (depending on car usage) and covered 2-3 calendar months of usage. ML model fitting was done using the Statistical and Machine Learning toolbox in MATLAB. Based on the results, the RUSBoosted Tree Ensemble shows a better performance than the other tested algorithms and demonstrated the most accurate results. Such an outcome can be also explained by the ability of the algorithm to overcome data imbalance. Figure 12 illustrates its validation accuracy for all available 100 vehicles, where an average accuracy of 73% has been achieved.

The analysis of model performance suggests that the behavior of some vehicles is more predictable (e.g., vehicles 12, 13, 15, 23, 26, 31, 99 demonstrate an accuracy of around 90%) than others (e.g., vehicles 9, 90, 81 demonstrate only around 60% accuracy). However, considering the mixture of drivers and the overall nature of driver behavior modelling complexity, the results are auspicious. The main outcome is that driving patterns can be leared from historical data, while the presence of some errors is acceptable. From a practical application viewpoint, the RUSBoosted Tree model acts as a white-box model, providing a significant advantage for real-world deployment. Moreover, the algorithm is efficient in terms of computational requirements, which make it suitable for integration into the ECU. Alternatively, all predictive models can be trained remotely on a cloud. In that case, each model can be easily represented as a set of rules defining split points and corresponding node values.

From a DPF health management viewpoint, the data-driven models provide input for an intelligent decision as outlined in Figure 9. Therefore, the next step assumes validation of driver behavior models as a part of the DPF optimization problem. The aim is to compare the benchmark strategy (regeneration is triggered once the DPF reaches State 3) with the proposed intelligent strategy, which uses input from the driver behavior model to support the DPF regeneration decision once State 3 is reached.

FIGURE 12 RUSBoosted Tree Ensemble prediction accuracy.



5.2. Performance Evaluation of the Proposed Intelligent DPF Health Management Strategy

To evaluate the efficiency of the proposed intelligent DPF health management framework, a simulation experiment in MATLAB was set up based on the journey history of the 100 vehicles. A surrogate soot accumulation model was used to predict the amount of soot generated per trip. It allowed to evaluate the average soot mass rate for each trip using the relevant vehicle parameters (i.e., parameters describing engine operation and affecting soot accumulation rate) available from the summarized trip statistics data set. Soot accumulation and regeneration cycles were built based on the sum of soot mass in the journey sequence, which is visualized in Figure 13. First, the model reproduced the behavior of the currently applied strategy, which keeps accumulating soot while the DPF is in State 1 to State 2 and attempts to regenerate at any journey once DPF State 3 is reached. Since data is very limited in information about the regeneration process, the following assumptions are applied to make the validation process as close to real-world behavior as possible:

1. It is assumed that 4 minutes of driving is required to evaluate the suitable conditions to attempt regeneration, which has been estimated (based on expert knowledge and engineering understanding of the system) as an average time to engine warm-up;
2. Taking the average time to deliver a successful regeneration, it is assumed that soot burning rate is constant and fixed for all regenerations.

In the next step, the proposed intelligent DPF control strategy was simulated, using the algorithm outlined in Figure 9. For this study, the State 3 to State 4 transition threshold was fixed for all simulation runs to an average value between these soot levels. Figure 14 illustrates an example of operation based on the proposed logic. As in the benchmark strategy, soot keeps accumulating until the system reaches State 3, where the decision model refers to the trip prediction model to find a suitable journey and then complete regeneration. This example shows how a sequence of predicted short trips postpone regeneration, and soot mass keeps growing, as observed by a pattern above the soot mass threshold. Once a correctly classified long trip occurs, successful regeneration restores the DPF filter back to State 1 (DPF empty) and a new soot accumulation cycle begins. However, if there is a long sequence of short trips or the model misclassifies long trips as short, DPF regeneration will not be attempted until the threshold for State 4 is reached—when regeneration will be attempted at every journey (Algorithm 1).

The proposed DPF control strategy was tested against the default strategy, across the sample of 100 vehicles, using the 25% of data reserved for validation, i.e., data that was unseen for the ML model training. However, since the validation data sequence (less than one month for some vehicles) does not cover sufficient soot accumulation and regeneration cycles for a meaningful validation experiment, the simulation repeated three times the journeys in the validation set. This approach not only ensured a long enough sequence of journeys but also allowed to add variability to DPF accumulation/regeneration cycles, as DPF regenerations were requested at different times/journeys. In effect, this enhanced the robustness of the validation experiment.

To evaluate the performance of the proposed DPF control strategy, the outputs of the validation simulation experiments were compared by taking the difference between the number of interrupted regenerations seen in the simulation of the proposed strategy versus the default one. Figure 15 presents the results of the evaluation, where improvement relates to the number of fewer attempted DPF regenerations seen in the simulation of the proposed control strategy. The results

FIGURE 13 Visualization of the benchmark control strategy.

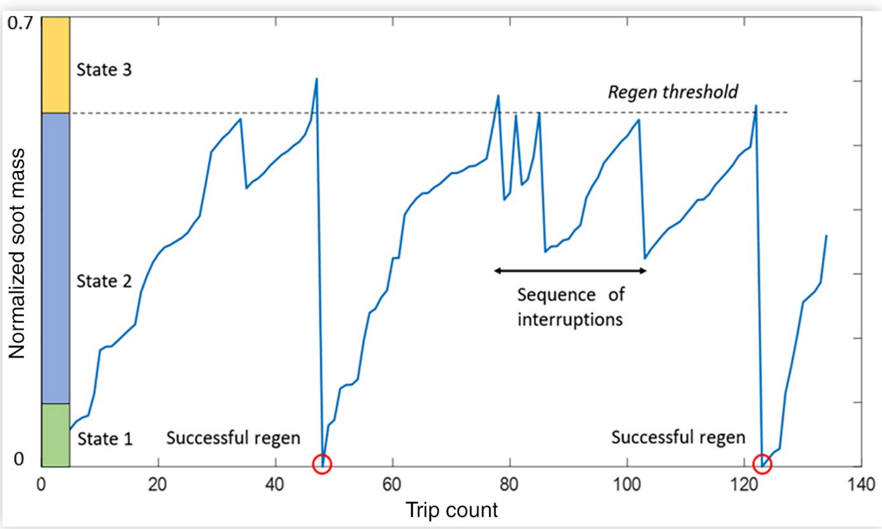
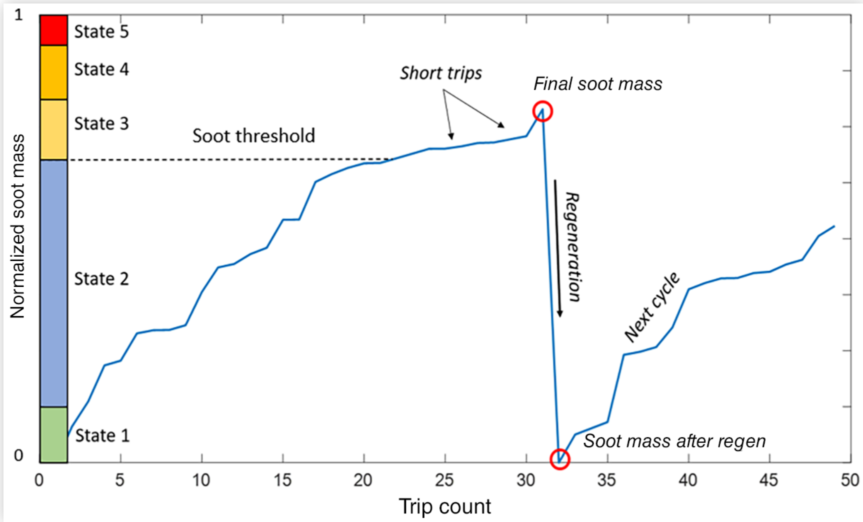


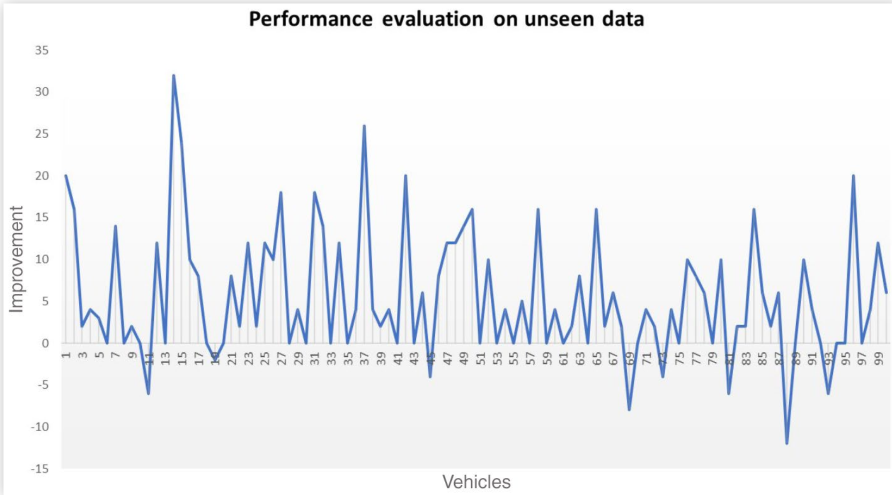
FIGURE 14 Visualization of the intelligent control strategy.



ALGORITHM 1 Simulation of the proposed DPF regeneration strategy.

```
Pseudo code:
m = accumulated soot mass
d = trip duration
m = 0
for i = 1: number of available trips
        if DPF in State 1 or State 2
                i = +1
        elseif DPF in State 3
                predict trip duration
                if predicted d(i) < X_cr & actual d(i) < X_cr
                postpone regeneration
                update m
                elseif predicted d(i) < X_cr & actual d(i) > X_cr
                        report missed opportunity to regenerate
                        update m
                elseif predicted d(i) > 15 & actual d(i) > X_cr
                        report successful regeneration
                        m = 0
                        start new cycle
                elseif predicted d(i) > 15 & actual d(i) < X_cr
                        report interrupted regeneration
                        update m (consider partial burning)
        elseif DPF in State 4
                attempt regeneration
                if actual d(i) < X_cr
                        report interrupted regeneration
                        update m (consider partial burning)
                else
                        report successful regeneration
                        m = 0
                        start new cycle
        elseif DPF in State 5
                request forced regeneration
                report incident
                m = 0
end
```

FIGURE 15 Performance evaluation of the intelligent regeneration control strategy.



provide conclusive evidence for the performance improvement achieved with the intelligent DPF regeneration strategy; as in most cases, there has been a reduction in the number of attempted regenerations. Across the fleet of 100 vehicles, the total number of interrupted events has reduced from 1176 to 548 cases, which represents a 53.7% improvement. From a health management perspective, this improvement will reflect not just in fuel economy and CO_2 reduction but will also have a positive effect on vehicle service interval, given the negative impact of attempted DPF regenerations on the oil condition.

However, Figure 15 also shows that for 8 out of 100 vehicles, a slight decrease in the DPF regeneration performance was observed. In all cases this was associated with a poor accuracy of the ML model, reflecting less predictable driving patterns for those vehicles. This is not surprising with real-world journeys data reflecting either irregular duty cycles or multiple users of the same vehicle.

6. Conclusions

This article presented the development and validation of an integrated framework for driving behavior modelling feeding predictive insight for intelligent powertrain control and health management strategies.

The proposed approach to driving behavior modelling combines features associated with the journey with specific driving behavior parameters to derive an ML model capable of predicting future (short term) behavior associated with parameters controlling damage accumulation. Unlike other approaches to driving behavior modelling, we do not consider navigation GPS data as this might not be always available, and hence not a universally robust input to powertrain health management or control. We have considered a range of classification ML models (listed in Table 1) in conjunction with a representative data set of real-world driving and found that an ensemble classifier (RUSBoosted Tree Ensemble, available in the MATLAB Machine Learning toolbox) provided the most robust models. Given the high and variable level of imbalance in the driving behavior data—both within the sequence of journeys for an individual vehicle and across the vehicle set—provides justification for this choice of ML model.

Upon evaluation of the validation accuracy of the ML model (Figure 12), it is apparent that the driving behavior of some vehicles can be more difficult to model accurately. While this can be explained by known heterogeneity in driving duty cycles (including the effect of multiple users for the same vehicle), the impact of low accuracy models is evident in the negative performance of the proposed intelligent control strategy (Figure 15). In practice, this could be addressed with a robust strategy where the intelligent control strategy is only adopted if the driving behavior ML model accuracy exceeds a certain threshold, thus ensuring performance can never be worse than the default strategy. From a modelling perspective, the quality of the model could be improved by allowing for larger training data sets, i.e., recognizing that it might take more than three months to "learn" the driving behavior of some vehicles. With larger training data sets, other ML modelling algorithms (including deep learning) might become feasible candidates. However, two important considerations should be maintained for the choice of ML models: (i) Computational efficiency—for online real-time implementation models that provide fast evaluation are preferred (the class of decision trees models fulfil this requirement); (ii) Robustness and explainability—while the proposed framework assumes a model fitted for each individual vehicle, adopting the same family of models across all vehicles would provide a sound argument for robustness, in particular if the choice of model can be explained with arguments (as illustrated in this article for the RUSBoosted Tree Ensemble).

The control strategy of the DPF operation, treated as a state-based reliability problem with integrated health management via the active DPF regenerations (regarded as maintenance actions in this context), provided a comprehensive illustration for the use of predictive driving behavior based on ML models to derive intelligent control strategies for powertrain performance and health management optimization. This approach can be extended to other similar problems where a reliability paradigm (either as damage accumulation or state based) can be employed. For the typical application of health management where the task revolves around predicting the RUL of a component or system, the driving behavior model provides the contextual information of expected future behavior, supporting prognostics and health management decision. However, from a powertrain point of view, as the DPF case study has illustrated, this framework can be applied to operational control strategies to enhance the vehicle performance (e.g., CO_2 reduction for the DPF case study) as well as reliability. For example, [96] discussed the use of predictive trip behavior to optimize the battery mode operation for a PHEV, showing potential significant reduction in engine starts for short journeys, with positive impact on both emissions an engine reliability.

In conclusion, this work has demonstrated the feasibility and significant potential of contextual intelligence for powertrain performance and health management improvement, based on the proposed framework for integrating predictive insight from data-driven driving behavior ML models with a reliability-based model of powertrain systems operation.

Acknowledgment

The authors acknowledge funding for the research presented in this article from Jaguar Land Rover under a research collaboration with the University of Bradford on "Intelligent Personalised Powertrain Healthcare," and the Institute of Digital Engineering who have provided funding for proof of concept—the aiR-FORCE project.

Contact Information

Aleksandr Doikin
adoikin2@bradford.ac.uk

References

1. Holland, S., "Integrated Vehicle Health Management in the Automotive Industry," in Smigorski, K., (eds.), *Health Management*, London: IntechOpen, 2010, https://doi.org/10.5772/9889.
2. Ahlfeld, R., "How to Save Virtual Prototyping Costs with Artificial Intelligence," Monolith AI Webinar, 2020.
3. Prajapati, A.K. and Roy, B.K., "A State of Art Review of Integrated Vehicle Health Management System," in *2018 3rd International Conference for Convergence in Technology (I2CT)*, Pune, India, 2018, IEEE, https://doi.org/10.1109/I2CT.2018.8529590.
4. Ofsthun, S., "Integrated Vehicle Health Management for Aerospace Platforms," *IEEE Instrumentation & Measurement Magazine* 5, no. 3 (2002): 21-24, https://doi.org/10.1109/MIM.2002.1028368.
5. Volponi, A.J., "Gas Turbine Engine Health Management: Past, Present, and Future Trends," *Journal of Engineering for Gas Turbines and Power* 136, no. 5 (2014): 051201, https://doi.org/10.1115/1.4026126.
6. Niculita, O., Nwora, O., and Skaf, Z., "Towards Design of Prognostics and Health Management Solutions for Maritime Assets," *Procedia CIRP* 59 (2017): 122-132, https://doi.org/10.1016/j.procir.2016.10.128.
7. Diaz-Elsayed, N., Hernandez, L., Rajamani, R., and Weiss, B.A., "Asset Condition Management: A Framework for Smart, Health-Ready Manufacturing Systems," in *International Manufacturing Science and Engineering Conference*, American Society of Mechanical Engineers, 2020, https://doi.org/10.1115/MSEC2020-8326.
8. Campean, F., Neagu, D., Doikin, A., Soleimani, M. et al., "Automotive IVHM: Towards Intelligent Personalised Systems Healthcare," in *Proceedings of the Design Society: International Conference on Engineering Design*, Cambridge University Press, 2019, https://doi.org/10.1017/dsi.2019.90.
9. Paris, D.E., Trevino, L.C., and Watson, M.D., "A Framework for Integration of IVHM Technologies for Intelligent Integration for Vehicle Management," in *2005 IEEE Aerospace Conference*, Big Sky, MT, 2005, IEEE, https://doi.org/10.1109/AERO.2005.1559691.
10. SAE International, "Design & Run-Time Information Exchange for Health-Ready Components," 2018, https://doi.org/10.4271/JA6268_201804.
11. Swearingen, K., Majkowski, W., Bruggeman, B., Gilbertson, D. et al., "An Open System Architecture for Condition Based Maintenance Overview," in *2007 IEEE Aerospace Conference*, Big Sky, MT, 2007, IEEE, https://doi.org/10.1109/AERO.2007.352921.
12. MIMOSA, "OSA-CBM V3.3.1 UML Model," Normative Information Specification, 2010.
13. Saxena, A., Roychoudhury, I., Goebel, K., and Lin, W., "Towards Requirements in Systems Engineering for Aerospace IVHM Design," in *AIAA Infotech@ Aerospace (I@ A) Conference*, Boston, MA, 2013, https://doi.org/10.2514/6.2013-4659.
14. Wilmering, T., *Integrated Vehicle Health Management-Systems of Systems Integration* (Warrendale, PA: SAE, 2017), https://doi.org/10.4271/PT-182.
15. Larsen, J.M., Christodoulou, L., Calcaterra, J.R., Dent, M.L. et al., "Integrated Systems Health Management: Enabling Technology for Effective Utilization of Air Vehicle Systems," in *Materials Damage Prognosis* Warrendale, PA: TMS (The Minerals, Metals & Materials Society), 2017, 47-51.
16. Eker, Ö.F., Camci, F., and Jennions, I.K., "Major Challenges in Prognostics: Study on Benchmarking Prognostic Datasets," in *1st European Conference of the Prognostics and Health Management Society* Dresden, Germany: PHM Society, 2012, https://doi.org/10.36001/phme.2012.v1i1.1409.

17. Wei, Z.G., Start, M., Hamilton, J., and Luo, L.M., "A Unified Framework for Representing Product Validation Testing Methods and Conducting Reliability Analysis," *SAE Int. J. Mater. Manf.* 9, no. 2 (2016): 303-314, https://doi.org/10.4271/2016-01-0269.
18. Sikorska, J., Hodkiewicz, M., and Ma, L., "Prognostic Modelling Options for Remaining Useful Life Estimation by Industry," *Mechanical Systems and Signal Processing* 25, no. 5 (2011): 1803-1836, https://doi.org/10.1016/j.ymssp.2010.11.018.
19. Saha, B. and Goebel, K., "Uncertainty Management for Diagnostics and Prognostics of Batteries Using Bayesian Techniques," in *2008 IEEE Aerospace Conference*, Big Sky, MT, 2008, IEEE, https://doi.org/10.1109/AERO.2008.4526631.
20. Atamuradov, V., Medjaher, K., Dersin, P., Lamoureux, B. et al., "Prognostics and Health Management for Maintenance Practitioners—Review, Implementation and Tools Evaluation," *International Journal of Prognostics and Health Management* 8, no. 3 (2017): 1-31, https://doi.org/10.36001/ijphm.2017.v8i3.2667.
21. Nguyen, V., Kefalas, M., Yang, K., Apostolidis, A. et al., "A Review: Prognostics and Health Management in Automotive and Aerospace," *International Journal of Prognostics and Health Management* 10 (2019): 1-35, https://doi.org/10.36001/ijphm.2019.v10i2.2730.
22. Tamssaouet, F., Nguyen, K.T., Medjaher, K., and Orchard, M.E., "Degradation Modeling and Uncertainty Quantification for System-Level Prognostics," *IEEE Systems Journal* 15, no. 2 (2020): 1628-1639, https://doi.org/10.1109/JSYST.2020.2983376.
23. Celaya, J.R., Saxena, A., and Goebel, K., "Uncertainty Representation and Interpretation in Model-Based Prognostics Algorithms Based on Kalman Filter Estimation," National Aeronautics and Space Administration Moffett Field CA Ames Research Center, 2012.
24. Smith, L. and Gal, Y., "Understanding Measures of Uncertainty for Adversarial Example Detection," arXiv preprint:1803.08533, 2018, https://doi.org/10.48550/arXiv.1803.08533.
25. Sankararaman, S., "Significance, Interpretation, and Quantification of Uncertainty in Prognostics and Remaining Useful Life Prediction," *Mechanical Systems and Signal Processing* 52 (2015): 228-247, https://doi.org/10.1016/j.ymssp.2014.05.029.
26. Petryna, Y., Link, M., and Künzel, A., "Modeling and Monitoring of Damage in Grouted Joints," in *6th European Workshop on Structural Health Monitoring*, Dresden, Germany, 2012.
27. Javed, K., Gouriveau, R., and Zerhouni, N., "State of the Art and Taxonomy of Prognostics Approaches, Trends of Prognostics Applications and Open Issues towards Maturity at Different Technology Readiness Levels," *Mechanical Systems and Signal Processing* 94 (2017): 214-236, https://doi.org/10.1016/j.ymssp.2017.01.050.
28. Doikin, A., Zadeh, E.H., Campean, F., Priest, M. et al., "Impact of Duty Cycle on Wear Progression in Variable-Displacement Vane Oil Pumps," *Procedia Manufacturing* 16 (2018): 115-122, https://doi.org/10.1016/j.promfg.2018.10.170.
29. Eker, O.F., Camci, F., and Jennions, I.K., "Physics-Based Prognostic Modelling of Filter Clogging Phenomena," *Mechanical Systems and Signal Processing* 75 (2016): 395-412, https://doi.org/10.1016/j.ymssp.2015.12.011.
30. Rebello, S., Yu, H., and Ma, L., "An Integrated Approach for System Functional Reliability Assessment Using Dynamic Bayesian Network and Hidden Markov Model," *Reliability Engineering & System Safety* 180 (2018): 124-135, https://doi.org/10.1016/j.ress.2018.07.002.
31. Cheng, Y., Zerhouni, N., and Lu, C., "A Hybrid Remaining Useful Life Prognostic Method for Proton Exchange Membrane Fuel Cell," *International Journal of Hydrogen Energy* 43, no. 27 (2018): 12314-12327, https://doi.org/10.1016/j.ijhydene.2018.04.160.
32. Marchegiani, L. and Posner, I., "Long-Term Driving Behaviour Modelling for Driver Identification," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, Maui, HI, 2018, IEEE, https://doi.org/10.1109/ITSC.2018.8569610.
33. Wang, Y. and Ho I.W.-H., "Joint Deep Neural Network Modelling and Statistical Analysis on Characterizing Driving Behaviors," in *2018 IEEE Intelligent Vehicles Symposium (IV)*, Changshu, China, 2018, IEEE, https://doi.org/10.1109/IVS.2018.8500376.
34. Stewart, M., "The Actual Difference between Statistics and Machine Learning," Towards Data Science, 2019.
35. Lei, Y., Li, N., and Lin, J., "A New Method Based on Stochastic Process Models for Machine Remaining Useful Life Prediction," *IEEE Transactions on Instrumentation and Measurement* 65, no. 12 (2016): 2671-2684, https://doi.org/10.1109/TIM.2016.2601004.
36. Si, X.-S., Wang, W., Hu, C.-H., and Zhou, D.-H., "Remaining Useful Life Estimation—A Review on the Statistical Data Driven Approaches," *European Journal of operational research* 213, no. 1 (2011): 1-14, https://doi.org/10.1016/j.ejor.2010.11.018.
37. Saxena, A., Prasad, M., Gupta, A., Bharill, N. et al., "A Review of Clustering Techniques and Developments," *Neurocomputing* 267 (2017): 664-681, https://doi.org/10.1016/j.neucom.2017.06.053.
38. Tzanakou, E.M., *Supervised and Unsupervised Pattern Recognition: Feature Extraction and Computational Intelligence* (Boca Raton, FL: CRC Press, 2017), https://doi.org/10.1201/9781420049770.
39. Abdi, H. and Williams, L.J., "Principal Component Analysis," *Wiley Interdisciplinary Reviews: Computational Statistics* 2, no. 4 (2010): 433-459, https://doi.org/10.1002/wics.101.
40. Ye, Z.S. and Xie, M., "Stochastic Modelling and Analysis of Degradation for Highly Reliable Products," *Applied Stochastic Models in Business and Industry* 31, no. 1 (2015): 16-32, https://doi.org/10.1002/asmb.2063.
41. Lei, Y., Li, N., Guo, L., Li, N. et al., "Machinery Health Prognostics: A Systematic Review from Data Acquisition to

RUL Prediction," *Mechanical Systems and Signal Processing* 104 (2018): 799-834, https://doi.org/10.1016/j.ymssp.2017.11.016.

42. Dey, A., "Machine Learning Algorithms: A Review," *International Journal of Computer Science and Information Technologies* 7, no. 3 (2016): 1174-1179.

43. Safavian, S.R. and Landgrebe, D., "A Survey of Decision Tree Classifier Methodology," *IEEE Transactions on Systems, Man, and Cybernetics* 21, no. 3 (1991): 660-674, https://doi.org/10.1109/21.97458.

44. Kotsiantis, S.B., Zaharakis, I., and Pintelas, P., "Machine Learning: A Review of Classification and Combining Techniques," *Artificial Intelligence Review* 26, no. 3 (2007): 159-190, https://doi.org/10.1007/s10462-007-9052-3.

45. Letham, B., Rudin, C., McCormick, T.H., and Madigan, D., "Interpretable Classifiers Using Rules and Bayesian Analysis: Building a Better Stroke Prediction Model," *Annals of Applied Statistics* 9, no. 3 (2015): 1350-1371, https://doi.org/10.1214/15-AOAS848.

46. Han, J., Pei, J., and Kamber, M., *Data Mining: Concepts and Techniques* (Amsterdam, the Netherlands: Elsevier, 2012), https://doi.org/10.1016/C2009-0-61819-5.

47. Fletcher, S. and Islam, M.Z., "Decision Tree Classification with Differential Privacy: A Survey," *ACM Computing Surveys (CSUR)* 52, no. 4 (2019): 1-33, https://doi.org/10.1145/3337064.

48. Gyamfi, K.S., Brusey, J., Hunt, A., and Gaura, E., "Linear Classifier Design under Heteroscedasticity in Linear Discriminant Analysis," *Expert Systems with Applications* 79 (2017): 44-52, https://doi.org/10.1016/j.eswa.2017.02.039.

49. Singh, A., Thakur, N., and Sharma, A., "A Review of Supervised Machine Learning Algorithms," in *2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom)*, New Delhi, India, 2016, IEEE.

50. Tharwat, A., Gaber, T., Ibrahim, A., and Hassanien, A.E., "Linear Discriminant Analysis: A Detailed Tutorial," *AI Communications* 30, no. 2 (2017): 169-190, https://doi.org/10.3233/AIC-170729.

51. Friedman, J.H., "Regularized Discriminant Analysis," *Journal of the American Statistical Association* 84, no. 405 (1989): 165-175, https://doi.org/10.1080/01621459.1989.10478752.

52. Gao, H. and Davis, J.W., "Why Direct LDA Is Not Equivalent to LDA," *Pattern Recognition* 39, no. 5 (2006): 1002-1006, https://doi.org/10.1016/j.patcog.2005.11.016.

53. Yu, H. and Yang, J., "A Direct LDA Algorithm for High-Dimensional Data—With Application to Face Recognition," *Pattern Recognition* 34, no. 10 (2001): 2067-2070, https://doi.org/10.1016/S0031-3203(00)00162-X.

54. Wen, J., Fang, X., Cui, J., Fei, L. et al., "Robust Sparse Linear Discriminant Analysis," *IEEE Transactions on Circuits and Systems for Video Technology* 29, no. 2 (2018): 390-403, https://doi.org/10.1109/TCSVT.2018.2799214.

55. Nikam, S.S., "A Comparative Study of Classification Techniques in Data Mining Algorithms," *Oriental Journal of Computer Science & Technology* 8, no. 1 (2015): 13-19.

56. Amra, I.A.A. and Maghari, A.Y., "Students Performance Prediction Using KNN and Naïve Bayesian," in *2017 8th International Conference on Information Technology (ICIT)*, Amman, Jordan, 2017, IEEE, https://doi.org/10.1109/ICITECH.2017.8079967.

57. Soria, D., Garibaldi, J.M., Ambrogi, F., Biganzoli, E.M. et al., "A 'Non-Parametric' Version of the Naive Bayes Classifier," *Knowledge-Based Systems* 24, no. 6 (2011): 775-784, https://doi.org/10.1016/j.knosys.2011.02.014.

58. Zheng, Z. and Webb, G.I., "Lazy Learning of Bayesian Rules," *Machine Learning* 41, no. 1 (2000): 53-84, https://doi.org/10.1023/A:1007613203719.

59. Kirchner, A. and Signorino, C.S., "Using Support Vector Machines for Survey Research," *Survey Practice* 11, no. 1 (2018): 2715, https://doi.org/10.29115/SP-2018-0001.

60. Lorena, A.C., Jacintho, L.F., Siqueira, M.F., De Giovanni, R. et al., "Comparing Machine Learning Classifiers in Potential Distribution Modelling," *Expert Systems with Applications* 38, no. 5 (2011): 5268-5275, https://doi.org/10.1016/j.eswa.2010.10.031.

61. Kataria, A. and Singh, M., "A Review of Data Classification Using k-Nearest Neighbour Algorithm," *International Journal of Emerging Technology and Advanced Engineering* 3, no. 6 (2013): 354-360.

62. Maclin, R. and Opitz, D., "Popular Ensemble Methods: An Empirical Study," arXiv: 1106.0257, 2011, https://doi.org/10.1613/jair.614.

63. Sagi, O. and Rokach, L., "Ensemble Learning: A Survey," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 8, no. 4 (2018): e1249, https://doi.org/10.1002/widm.1249.

64. Seiffert, C., Khoshgoftaar, T.M., Van Hulse, J., and Napolitano, A., "RUSBoost: A Hybrid Approach to Alleviating Class Imbalance," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* 40, no. 1 (2010): 185-197, https://doi.org/10.1109/TSMCA.2009.2029559.

65. Mounce, S., Ellis, K., Edwards, J., Speight, V. et al., "Ensemble Decision Tree Models Using Rusboost for Estimating Risk of Iron Failure in Drinking Water Distribution Systems," *Water Resources Management* 31, no. 5 (2017): 1575-1589, https://doi.org/10.1007/s11269-017-1595-8.

66. Chawla, N.V., Lazarevic, A., Hall, L.O., and Bowyer, K.W., "SMOTEBoost: Improving Prediction of the Minority Class in Boosting," in *European Conference on Principles of Data Mining and Knowledge Discovery*, Springer, Berlin, Heidelberg, 2003, https://doi.org/10.1007/978-3-540-39804-2_12.

67. Schapire, R.E., "Explaining Adaboost," in *Empirical Inference*, Springer, Berlin, Heidelberg, 2013, 37-52, https://doi.org/10.1007/978-3-642-41136-6_5.

68. Chen, Y.-Y., Lin, Y.-H., Kung, C.-C., Chung, M.-H. et al., "Design and Implementation of Cloud Analytics-Assisted

Smart Power Meters Considering Advanced Artificial Intelligence as Edge Analytics in Demand-Side Management for Smart Homes," *Sensors* 19, no. 9 (2019): 2047, https://doi.org/10.3390/s19092047.

69. Li, H., Liu, Z., Liu, K., and Zhang, Z., "Predictive Power of Machine Learning for Optimizing Solar Water Heater Performance: The Potential Application of High-Throughput Screening," *International Journal of Photoenergy* 2017 (2017): 1-10, https://doi.org/10.1155/2017/4194251.

70. Li, H., Zhang, Z., and Liu, Z., "Application of Artificial Neural Networks for Catalysis: A Review," *Catalysts* 7, no. 10 (2017): 306, https://doi.org/10.3390/catal7100306.

71. Hamadache, M., Jung, J.H., Park, J., and Youn, B.D., "A Comprehensive Review of Artificial Intelligence-Based Approaches for Rolling Element Bearing PHM: Shallow and Deep Learning," *JMST Advances* 1, no. 1 (2019): 125-151, https://doi.org/10.1007/s42791-019-0016-y.

72. LeCun, Y., Bengio, Y., and Hinton, G., "Deep Learning," *Nature* 521, no. 7553 (2015): 436-444, https://doi.org/10.1038/nature14539.

73. Ng, A., "What Data Scientists Should Know about Deep Learning," in *Extract Data Conference*, San Francisco, CA, 2015.

74. Khan, S. and Yairi, T., "A Review on the Application of Deep Learning in System Health Management," *Mechanical Systems and Signal Processing* 107 (2018): 241-265, https://doi.org/10.1016/j.ymssp.2017.11.024.

75. Zhao, R., Yan, R., Chen, Z., Mao, K. et al., "Deep Learning and Its Applications to Machine Health Monitoring," *Mechanical Systems and Signal Processing* 115 (2019): 213-237, https://doi.org/10.1016/j.ymssp.2018.05.050.

76. Gutjahr, T., "Performance Analysis of Data-Driven Plant Models on Embedded Systems," SAE Technical Paper 2016-32-0086, 2016, https://doi.org/10.4271/2016-32-0086.

77. Singh, N., Rutland, C.J., Foster, D.E., Narayanaswamy, K. et al., "Investigation into Different DPF Regeneration Strategies Based on Fuel Economy Using Integrated System Simulation," SAE Technical Paper 2009-01-1275, 2009, https://doi.org/10.4271/2009-01-1275.

78. Bai, S., Tang, J., Wang, G., and Li, G., "Soot Loading Estimation Model and Passive Regeneration Characteristics of DPF System for Heavy-Duty Engine," *Applied Thermal Engineering* 100 (2016): 1292-1298, https://doi.org/10.1016/j.applthermaleng.2016.02.055.

79. Tong, D., Zhang, J., Wang, G., Yang, B. et al., "Experimental Study and Numerical Interpretation on the Temperature Field of DPF during Active Regeneration with Hydrocarbon Injection," SAE Technical Paper 2018-01-1257, 2018, https://doi.org/10.4271/2018-01-1257.

80. Kotrba, A., Bai, L., Yetkin, A., Shotwell, R. et al., "DPF Regeneration Response: Coupling Various DPFs with a Thermal Regeneration Unit to Assess System Behaviors," SAE Technical Paper 2011-01-2200, 2011, https://doi.org/10.4271/2011-01-2200.

81. Chen, K., Martirosyan, K.S., and Luss, D., "Temperature Gradients within a Soot Layer during DPF Regeneration," *Chemical Engineering Science* 66, no. 13 (2011): 2968-2973, https://doi.org/10.1016/j.ces.2011.03.037.

82. Doikin, A., "Automotive IVHM: A Framework for Intelligent Health Management of Powertrain Systems," PhD thesis, University of Bradford, 2020.

83. Tadrous, T.N., Brown, K., Towgood, P., and McConnell, C., "Development of Passive/Active DPF System Utilizing Syngas Regeneration Strategy - Retrofit, Real Life Optimization and Performance Experience," SAE Technical Paper 2010-01-0560, 2010, https://doi.org/10.4271/2010-01-0560.

84. Chiavola, O., Chiatti, G., and Sirhan, N., "Impact of Particulate Size during Deep Loading on DPF Management," *Applied Sciences* 9, no. 15 (2019): 3075, https://doi.org/10.3390/app9153075.

85. Kontses, D., Geivanidis, S., Fragkiadoulakis, P., and Samaras, Z., "Uncertainties in Model-Based Diesel Particulate Filter Diagnostics Using a Soot Sensor," *Sensors* 19, no. 14 (2019): 3141, https://doi.org/10.3390/s19143141.

86. Kianifar, M.R., Campean, F., Beattie, T., and Richardson, D., "Analytical Target Cascading Framework for Diesel Engine Calibration Optimisation," SAE Technical Paper 2014-01-2583, 2014, https://doi.org/10.4271/2014-01-2583.

87. Di Sarli, V. and Di Benedetto, A., "Modeling and Simulation of Soot Combustion Dynamics in a Catalytic Diesel Particulate filter," *Chemical Engineering Science* 137 (2015): 69-78, https://doi.org/10.1016/j.ces.2015.06.011.

88. Barba, F., Vassallo, A., and Greco, V., "Estimation of DPF Soot Loading through Steady-State Engine Mapping and Simulation for Automotive Diesel Engines Running on Petroleum-Based Fuels," SAE Technical Paper 2017-24-0139, 2017, https://doi.org/10.4271/2017-24-0139.

89. Dawei, Q., Jun, L., and Yu, L., "Research on Particulate Filter Simulation and Regeneration Control Strategy," *Mechanical Systems and Signal Processing* 87 (2017): 214-226, https://doi.org/10.1016/j.ymssp.2016.05.039.

90. Castellano, J., Chaudhari, A., and Bromham, J., "Adaptive Temperature Control for Diesel Particulate Filter Regeneration," SAE Technical Paper 2013-01-0517, 2013, https://doi.org/10.4271/2013-01-0517.

91. Hopka, M., Upadhyay, D., and Van Nieuwstadt, M., "Smart DPF Regenerations - A Case Study of a Connected Powertrain Function," *SAE Int. J. Adv. & Curr. Prac. in Mobility* 1, no. 2 (2019): 762-770, https://doi.org/10.4271/2019-01-0316.

92. Doikin, A., Campean, F., Neagu, D., Priest, M. et al., "Knowledge-Enabled Machine Learning for Predictive Diagnostics: A Case Study for an Automotive Diesel Particulate Filter," in *Proceeding of 30th European Safety and Reliability Conference and 15th Probabilistic Safety Assessment and Management Conference*, Venice, Italy, 2020, https://doi.org/10.3850/978-981-14-8593-0_5573-cd.

93. Torgunov, D., Trundle, P., Campean, F., Neagu, D. et al., “Vehicle Warranty Claim Prediction from Diagnostic Data Using Classification,” in *UK Workshop on Computational Intelligence*, Springer, Cham, 2019, https://doi.org/10.1007/978-3-030-29933-0_40.

94. Shaojun, H., Jin, C., Ruixu, G., and Guijun, W., “The Capability Analysis on the Characteristic Selection Algorithm of Text Categorization Based on F1 Measure Value,” in *2012 Second International Conference on Instrumentation, Measurement, Computer, Communication and Control*, Hangzhou, China, 2012, IEEE, https://doi.org/10.1109/IMCCC.2012.180.

95. Sokolova, M., Japkowicz, N., and Szpakowicz, S., “Beyond Accuracy, F-Score and ROC: A Family of Discriminant Measures for Performance Evaluation,” in *Australasian Joint Conference on Artificial Intelligence*, Springer, Berlin, Heidelberg, 2006, https://doi.org/10.1007/11941439_114.

96. Angiolini, E. and Campean, F., “aiR-FORCE Proof of Concept, Digital Webinar Series—Demonstrating the Art of Possible,” Institute of Digital Engineering, May 19, 2021, accessed Dec. 2021, https://www.ide.uk/post/digitalisation-webinar-series-demonstrating-the-art-of-the-possible.

97. Doikin, A., Campean, F., Priest, M., Lin, C. et al., “A Reliability Inspired Strategy for Intelligent Performance Management with Predictive Driver Behaviour: A Case Study for a Diesel Particulate Filter,” *Proceedings of the Design Society* 1 (2021): 191-200, https://doi.org/10.1017/pds.2021.20.