Deep Learning Gas Engine Health Assessment

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Abstract: With the objective to reduce greenhouse emissions, efforts have gone to increase the integration of alternative fuels such as natural gas in the transportation sector. Using natural gas as automobile fuel has several advantages over petrol and diesel: lower costs, better combustion efficiency, and the possibility to produce it through a biomass conversion process. Natural gas-based engines have become a crucial asset in the South American transportation sector. However, the share of natural-gas vehicles in the current vehicle market is still estimated to be below 5%. Therefore, to incentivize investments and development in gas engines, it is imperative to ensure their reliability, availability, and sustainability; by developing reliability analysis and identifying critical components, probability of failure, and better operating conditions. These assessments can later be used to design tailored maintenance policies, thus reducing maintenance and operational costs. This paper presents a deep learning-based prognostics analysis for gas engines from a fleet of heavy-duty trucks (HDTs) from a Colombian company. These HDTs operate under varying demand profiles, including continuous stops and runs, long trajectories, steep hills, and frequent load-unload cycles. The dataset presents two challenges during the preprocessing stage, namely: the raw dataset does not include any kind of labels, and the sensors present an irregular sampling frequency. Thus, the analysis on this paper focuses on addressing these preprocessing challenges to later train prognostics models for the remaining useful life (RUL) estimation of the gas engine fleet. Results show that by implementing an adequate preprocessing methodology, promising results can be obtained for the engine's RUL.

1. INTRODUCTION

In last decades, governments have been concerned about establishing regulations that favour the reduction of greenhouse gas (GHG) emissions. For instance, the Paris Agreement, ratified by 174 countries in 2016, aims to substantially reduce global GHG emissions to limit the global temperature increase to 2°C above preindustrial levels [1]. One of the alternatives to achieve this environmental objective is reducing GHG emissions by 50% by 2050. Nevertheless, this implies a decarbonization rate of approximately 5% per year, sustained over 40 years [2].

Particularly, transportation is routinely identified as one of the most difficult sectors to decarbonize, while improvements in energy efficiency have been offset by increasing transport volumes and distances [3]. In this regard, Chiaramonti & Goumas [4] state that alternative and renewable transport fuels, grouping both advanced biofuels and recycled carbon fuels, will be key routes for the decarbonization of transports. As an example, the aviation industry has been adopting the Sustainable Aviation Fuel (SAF) as an alternative to decarbonization [5], and Since 2008, SAF has powered over 250,000 flights around the world [6]. Further, the maritime industry directs its efforts to increase the

Energy Efficiency Design Index (EEDI) by designing ships using lower-carbon fuels such as biofuels, Liquefied Natural Gas (LNG), and hydrogen. On the other hand, the automotive industry has adopted similar policies by prompting natural gas as a promising fuel alternative, and even when LNG is considered a fossil fuel, different studies have found that diesel engines emitted five times more NOx (nitrogen dioxide and nitric oxide) emissions than Natural Gas Vehicles (NGVs) [7], [8].

Considering the need to establish adequate maintenance polices for these engines, there has been an interest by the operators, users, and manufacturers of these assets in the execution of prognostics and health management (PHM) analysis. PHM seeks to provide accurate information on a system's state of health by means of end-to-end frameworks. Propelled by massive data sets acquired from monitoring sensor networks, researchers have lately focused on using data-driven models (DDMs) to analyze condition-monitoring data collected from sensor networks. In this regard, several machine learning (ML) and deep learning (DL) algorithms have been implemented for diagnostics and prognostics tasks. For instance, in diagnostics, convolutional neural networks (CNNs) and their variations have been used to locate and estimate the damage in structural systems [9], [10]. On the other hand, prognostics frameworks commonly focus on the estimation of the system's remaining useful life (RUL). Here, several ML and DL architectures have been proposed and tested such as long short-term memory (LSTM) cells [11], physics-informed neural networks (PINN) [12], however, very few have successfully been applied to real life complex systems [13]. Rather, DL-PHM frameworks are usually validated on data sets obtained from numerical simulation, or experimental rigs. Hence, these datasets do not contain many of the problems that can be presented in data collected from sensor in real system, such as noisy environments, missing data logs, redundant sensors, and external influences.

In this context, this paper presents a DL-based methodology based for fault prognostics for a real system. The system consists of a gas engine installed on a Heavy-Duty Truck (HDT) fleet of a Colombian company. Particularly, these HDT's operate under demanding conditions, including continuous stops and runs, long trajectories up to the company's facilities, steep hills, and frequent load-unload cycles.

The remainder of this paper is structured as follows: Section 2 details the operational and technical characteristics of gas engine analyzed during the study. Section 3 presents the methodology proposed to predict the failure of a real HDT, describing the main challenges faced when analyzing a real system. The obtained results and their discussion are presented in Section 4. Lastly, Section 5 exposes the main conclusions and remarks of this study.

2. GAS ENGINE

In functional terms, a gas engine is a type of internal combustion engine, which is responsible for transforming the fuels' chemical energy into heat, and later into mechanical energy [14]. In this study, an in-line gas six-cylinder engine is studied. The engine uses a three-way catalyst which works by introducing a catalyst to convert the nitrogen oxides to nitrogen gas and oxygen gas, carbon monoxide to carbon oxide, and hydrocarbons to carbon dioxide and water. The engine also has direct injection, turbocharged and Stoichiometric cooled Exhaust Gas Recirculation (SEGR). Table 1 presents the main technical characteristics of the engine under study.

Table 1: Main technical characteristics of engine gas under study

Number of cylinders and position	6 cylinders in line
Maximum power	320 HP
Maximum torque	1000 LB-FT
RPM at full power	2200 RPM
Injection	Electronics
Operating cycles	4
Fuel type	CNG/LNG/RNG

Fuel autonomy	240 Km
Fuel efficiency	1.75 Km/M3

Furthermore, according to the manufacturer, this kind of commercial engine has been used in a variety of vehicle applications as school buses, urban transit, vocational and medium-duty trucks, and tractors. In particular, the gas engine under study is installed on HDTs, which are used to collect and compact solid waste in a Colombian city.

In this regard, operational data is collected between January 2019 to June 2020. Maintenance reports of the asset are also provided, which revealed 22 relevant failures on the engine during the same operational period. The challenges presented by this data set when using it for prognostics purposes are twofold. First, the data set is unlabeled, i.e., for each record, the vehicle's operational information is synthesized in 14 variables (see Table 2), but it is unknown whether this record corresponds to a healthy or degraded state of the system. Second, the collected sensor data set presents a non-constant sampling time, since each sensor is programmed to collect data at different time intervals. The next section exposes the methodology proposed to face these challenges.

Table 2: Operational variables of gas engine under study

Abbreviation	Description	Unit	Operational Parameters	
			Minimum	Maximum
Altitude	The point reached by the vehicle in relation to sea level	meter	1100	1750
ODOM	Number of kilometres travelled by the vehicle (accumulated)	km	0	NA
ECT	Temperature reached by the coolant	ºC	70	100
RPM	Describes the rate at which the rotor is revolving, which is the number of times the rotor shaft completes a full rotation each minute	rpm	150	2200
ETBP	Turbo pressure	kPa	10	25
EIMT	Air intake temperature	ºC	60	120
TH	Number of hours operated by the vehicle (accumulated)	horas	0	NA
WVS	Speed reached by the vehicle	km/h	70	92.8
FDS	Fan Status	states	0	1
APP	Accelerator pedal position	%	0	100
ECL	Coolant level	%	80	100
EOP	Oil pressure	kPa	69	207
CC2	Cruise mode enabled	states	0	1
CC3	Brake pedal status	states	0	1

3. METHODOLOGY

Several challenges must be faced when applying DL models to PHM for real complex systems [13], [15]. As previously commented, in the presented the gas engine case study, two preprocessing challenges need to be addressed. This section details the proposed process to analyze the data and perform the PHM analysis. Figure 1 shows the proposed methodology.

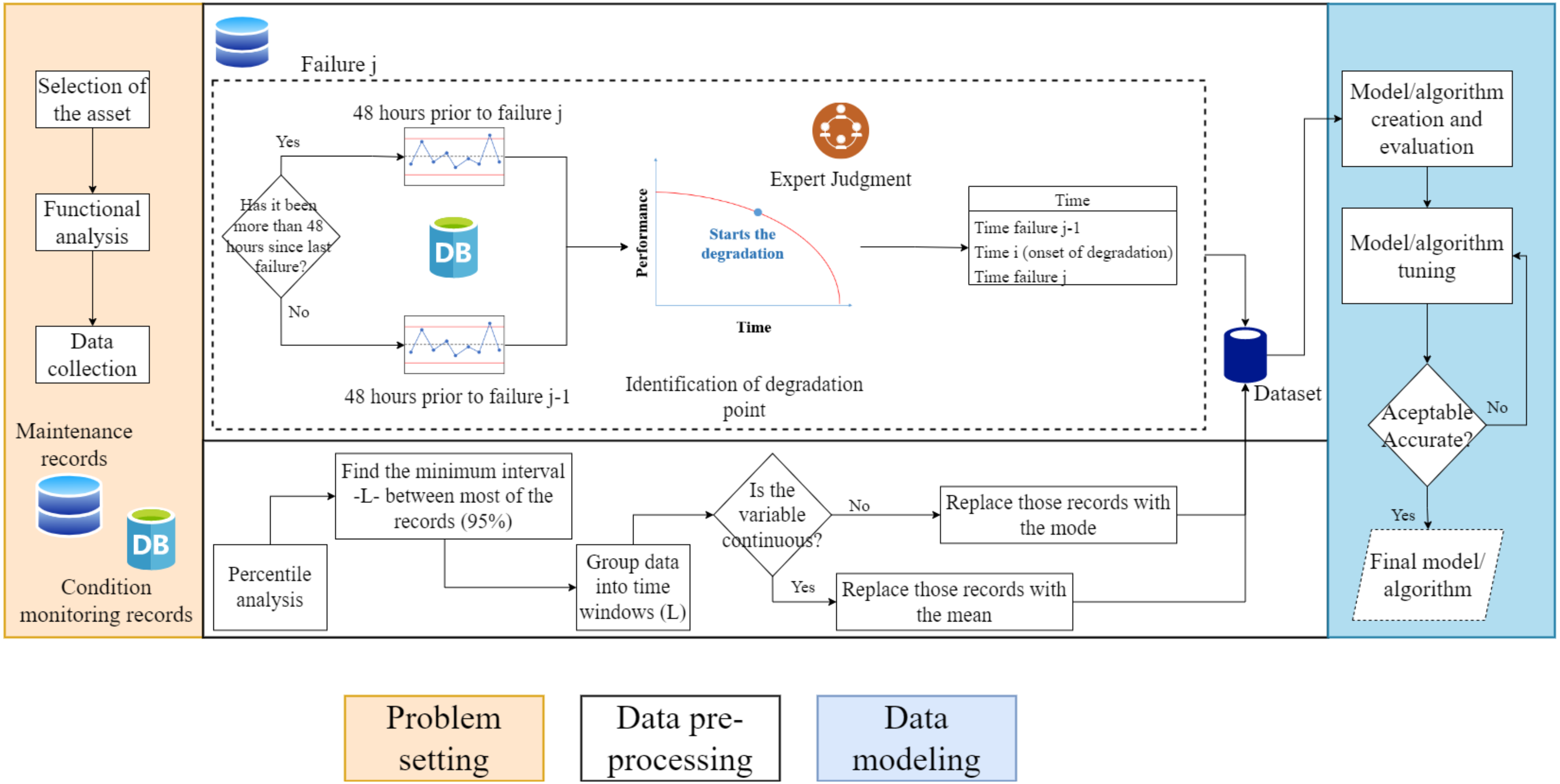

Figure 1: Proposed methodology

The analysis is divided into three phases. First, the problem is characterized, i.e., all the available technical and operational information about the selected asset is gathered. In the case of the solid waste management company, the selected HDT corresponds to a vehicle of interest because it is a generic vehicle of the fleet and their hazard rate is in the second region of the bathtub curve [16], ensuring that the registered failures correspond to random event rather than wear out or infant mortality. Two databases are provided for the vehicle under study. A database with vehicle condition monitoring records without specifying the vehicle's operational status (operational, degraded or in failure), and second database with detailed information regarding repairs performed on the vehicle. These databases represent the theoretical basis for the second phase of the methodology.

The data preprocessing phase is divided into two stages. The first stage corresponds to the data labeling, which is illustrated in the upper central part of Figure 1. Initially, it was identified from the maintenance records that 43% of the failures recorded between January 2019 and June 2020 were due to failures in the cooling system, particularly in the radiator, and the second critical system was the gas engine, with 42% of the reported failures.

Nevertheless, a company maintenance policy showed that these failures could have been assigned to the wrong system or components, due to the company required the maintenance team to carry out the repairs within a maximum time of 3 hours, arguing that this would guarantee high availability of vehicle. This maintenance policy had a side effect which was that the mechanics worked on the symptoms of the failure and not the causes, so, for example, the maintenance records described recurrent radiator failure and a few days later the records presented detailed reports of the cause in the gas engine system.

In view of this scenario, it is of interest to identify the vehicle's degradation points start and not only the failure event. In this regard, each of the reported failures is analyzed regardless of the vehicle system previously assigned to the failure. If failure j was reported 48 or more hours after the last failure $(j-1)$, then from the vehicle's operating conditions, a temporal plot is drawn with each of the 14 operational variables (see Table 2) of the 48 hours prior to the failure, and a team of experts established the time instant at which one or more variables presented a different behavior than expected, thus showing the beginning of the asset's degradation. On the other hand, if failure j was reported less than 48 hours after a repair, then the expert team needed to analyze the vehicle's operational behavior from 48 hours before the previous failure $(j-1)$ to failure j, as it could be a failure record assigned to the wrong system.

For example, Figure 2 shows one of the variables analyzed during the study of one of the engine failures. This variable presents an increase in the temperature reached by the coolant a few hours before the failure. Considering that the technical specifications establish that the maximum temperature reached by the coolant should be 100 ºC, this behavior suggests an abnormality of the engine performance.

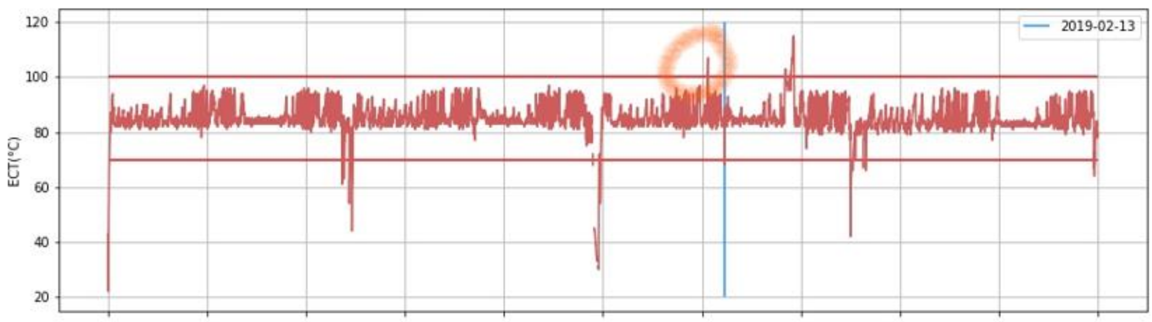

Figure 2: Example of a variable analyzed during the study of an engine failure

Thus, for each failure j the team of experts discussed from different points of view the relationship between the behavior of the variables and the type of failure reported by the maintenance team, to identify the abnormal behavior of the data that evidenced the beginning of the degradation of the system.

The team of experts was composed by two members of the vehicle's operational team, two members of the maintenance team, an expert in reliability of mechanical systems and two experts in data analytics.

Once the experts identified the time of onset the degradation, the data were labeled as follows:

- Operational state: records reported between the first record after the failure $j-1$ and the time i at which the vehicle's degradation starts if failure j was reported 48 or more hours after the last failure $(j-1)$; or records reported between the first record after the failure $j-2$ and the time i at which the vehicle's degradation starts if the failure j was reported less than 48 hours before the previous failure $(j-1)$.
- Degraded state: records reported between the time i at which the vehicle's degradation starts and the reported time of failure j.
- Failure state: record at which the failure was reported, for this state there is only one record for each failure, given that during sensors are turned off during the system's repair.

Regarding the second approach (step by step shown in the lower central part of Figure 1), the sensors' sampling time needs to be uniform. Therefore, a percentile analysis is developed to identify the minimum interval in which 95% of the data are collected. Among the minimum interval identified for each sensor, then the maximum interval is selected as sampling frequency for the data. For each time window, records are replaced for the average if the variable is continuous or for the mode if the variable was categorical.

Figure 3 presents an example of the proposed process to resolve the irregular sampling time. Note that each sensor is monitored in different time deltas, that is, the first sensor shows records for each time t_i, but the second sensor shows records every t_{i+2}, while the third sensor only shows records every t_{i+4}. Thus, it is proposed to identify the minimum interval representing 95% of the data collected by each sensor. As an example, let us suppose that the minimum interval for the first sensor is $\Delta = i+1$, $\Delta = i+2$ for the second sensor, and $\Delta = i+4$ for the third sensor. Then, the maximum interval is selected between these intervals and time windows are generated according to the previously presented recommendations.

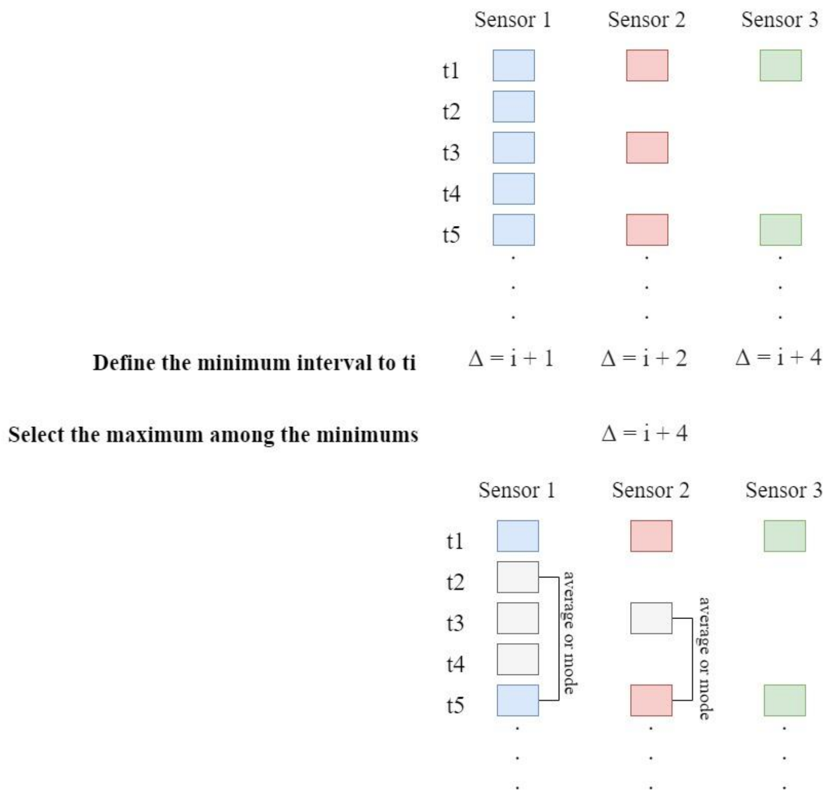

Figure 3: Example for percentile analysis of irregular sampling frequency

The data preprocessing phase results in a consolidated database with labeled data for two system states (operational or degraded), with a uniform sampling frequency every 35 seconds, and an additional column with the estimated RUL at each record collected.

Note that at the moment of failure, the RUL is equal to zero and for the data collected in the previous times, the RUL starts to increase. Therefore, on historical data the RUL calculation is obtained as the difference between the current time and the time of the future failure.
Finally, the third phase consists of data modeling to predict the RUL of the gas engine. A deep neural network (DNN) model is designed and trained, the hyperparameters are tunning until obtain an acceptable accurate. The consolidated dataset was divided 85% to train and 15% to test. The hyperparameters used for the neural network and its training process are presented on
Table **3**.

Table 3: Neural network hyperparameters

Training hyperparameters	
Epochs	150
Learning rate	0.0001
Loss function	Mean squared error
Optimizer	Adam
Batch size	100
Architecture hyperparameters	
Hidden layers	6
Neurons	[256, 128, 64, 32, 16, 8]
Activation function	Relu

4. RESULTS AND DISCUSSION

The proposed methodology is applied to analyze a gas engine used by HDT fleet of a solid waste management company. As previously commented, the first phase of the methodology concluded in three results:

- Selection of a key asset for the company and feasible for the study,
- Data collection obtained from two databases (maintenance records and operational condition records),
- A functional analysis of kind of engine under study.

Figure 4 shows the functional tree of an internal combustion engine. In general terms the internal combustion engine, like gas engine, is composed of six systems: starter, combustion engine unit, crankshaft system, control system, lubrication system and cooling system.

The starter is responsible for rotating the engine to initiate the engine's operation under its own power. The combustion engine unit transforms chemical energy into mechanics to generate shaft power. Crankshaft system transmits axis rotational power [17]. Control system have two functions, which are monitors and controls the operational signals inside the engine. Lubrication system maintains proper lubricating conditions of combustion engine unit whereas cooling system maintains at the appropriate temperature for the operation of the combustion engine unit [18].

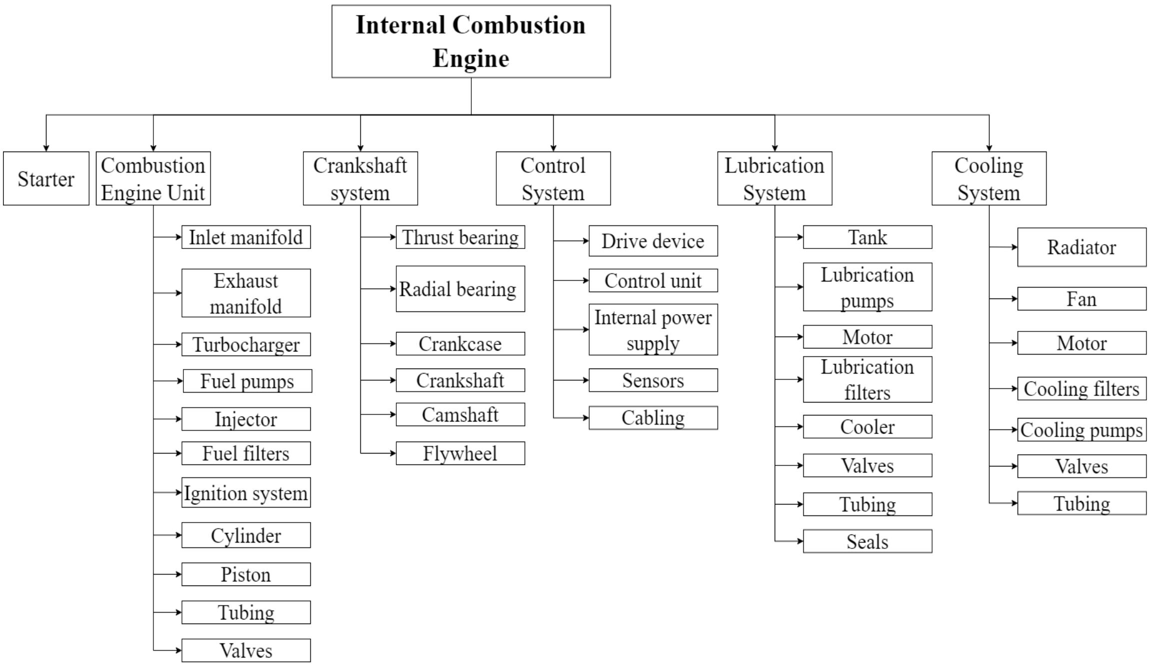

Figure 4: Functional tree of combustion internal engine

Regarding the second phase of the methodology, the main results is the consolidated database obtained from the pre-processing process. Nevertheless, during the data analysis, the impact of maintenance polices on the operational performance of assets was highlighted. For instance, Figure 5 presents the HDT's RUL before the expert judgement. Note that in some temporal spaces there are recurrent values of RUL less than 50 hours because in these cases the maintenance team was working on the symptom and not on the real causes of the HDT failure.

It is worth noting that, once the expert judgement is performed, the consolidated dataset considered only gas engine failures, to train the neural network to predict the gas engine's RUL.

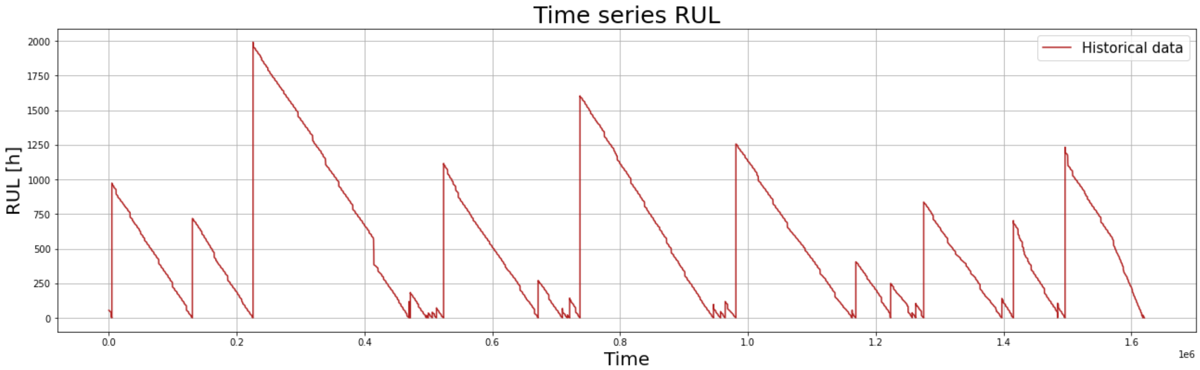

Figure 5: HDT's RUL before expert judgement

The data modeling phase allowed training and testing the neural network to ensure an adequate prediction of the RUL of the gas engine. Table 4 presents the average root mean squared error (RMSE) obtained with the trained neural network for the consolidated dataset, and the RUL average for each dataset.

Table 4: RUL RMSE values vs RUL average for training and testing dataset [hours]

	Training	Test
RMSE	52.58	55.04
RUL average	546.91	545.79

Figure 6 presents the training and validation cost throughout the training process. Here, it can be observed that both curves present an identical behavior, and the lines converges to the same cost value, concluding that the trained model have good generalization capabilities.

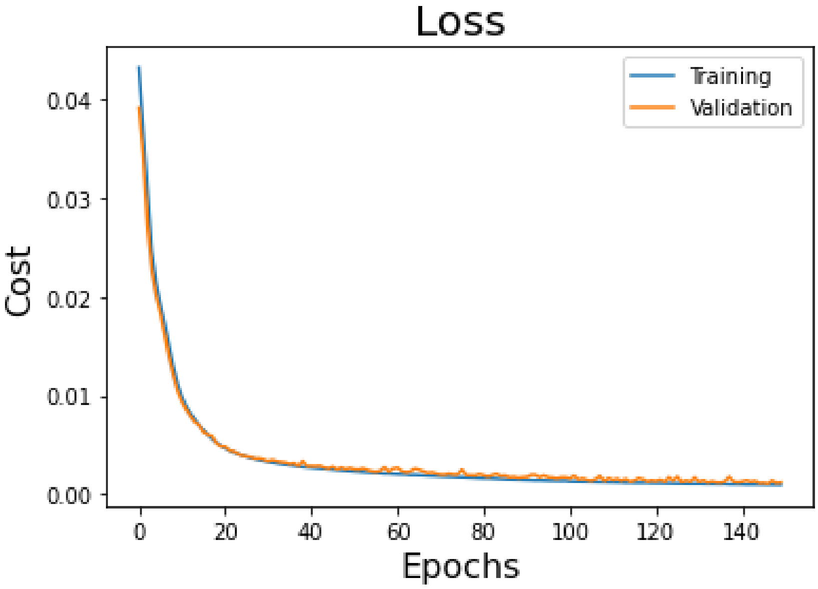

Figure 6: Training and validation cost value per number of epochs during the training process

Finally, Figure 7 compares the predicted RUL values with the actual values for the training and testing datasets. In general, the predicted data follow the real behavior, however there are some temporal points where the predicted RUL value is lower than the real one. This would generate, in practice, a preparation of the maintenance team long before the failure occurs.

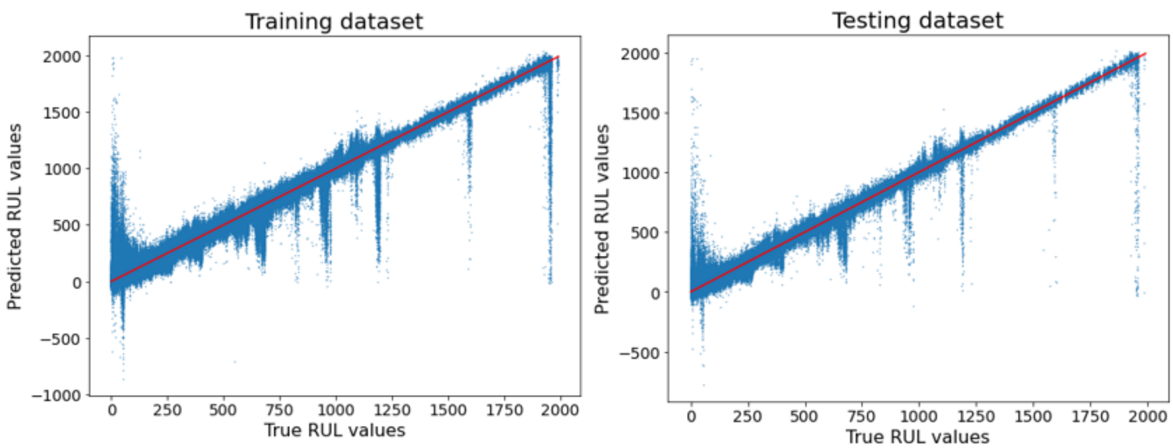

Figure 7: RUL training and testing data predictions

5. CONCLUSIONS

This paper presents a methodology based on deep learning techniques to perform a gas engine health assessment, using a real case study. The proposed methodology presents alternatives to overcome common challenges in data preprocessing from real engineering systems, such as the analysis from unlabeled data and data with irregular sampling frequency. Furthermore, the authors present a functional study of internal combustion engine, to provide technical and operational information on this type of engines.

This study allows for methodological and practical conclusions. That is, in practical terms, the study showed the relevance of data analysis to evaluate the side effects of strategic decisions on the company's assets, because in the case study, the preliminary data analysis showed that there were some recurrent failures due to the maintenance team in some situations it took more than 3 hours to find the root cause of the vehicle failure. In addition, the study allows the maintenance team to prepare for HDT's gas engine failures knowing that these types of failures occur every 544.07 hours on average.

In methodological terms, the authors recognize that there are still important challenges that need to be faced in the application of DL-PHM models in real life. Therefore, it is recommend involving the operational and maintenance team of the system during the initial phases of the study (problem setting and data pre-processing), as this practice ensures greater knowledge of the particular conditions of the system under study.

In the future, other deep learning techniques could be used to compare the prediction of RUL in gas engine.

Acknowledgements

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