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CONDITION MONITORING WITH PREDICTION BASED ON OIL ENGINES OF URBAN BUSES – A CASE STUDY

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ABSTRACT

The paper presents a case study and a model for condition monitoring of Diesel engines' oil of urban buses, through the accompaniment of the evolution of its degradation, with the objective to implement a predictive maintenance policy.

Along time, because the usage, there is some decay in the lubricant properties. However, in normal functioning conditions, the lubricants properties, at the time the manufacturers recommend its changing, regardless of they are within the safety limits. Then, based on the accompaniment of the lubricants' oil condition, the intervals of oil replacement can be enlarged what implies the availability increasing and the corresponding production increasing of the equipment.

The model presented in this paper shows its potential to be spread to other types of equipment and organisations that want can implement similar maintenance policies, to achieve the best availability based on the real equipment health conditioning conditions.

Keywords: Condition monitoring; Predictive maintenance; Oil analysis; Urban buses.

1. INTRODUCTION

Public transport, in general, and the city bus passenger transport, in particular, represents an important alternative to the use of individual transport. For this reason, it is essential to focus on the quality of service provided by the public transport network in order to make them attractive for its users.

Under the current context, where the users of public transport are increasingly demanding about the quality of services, the maintenance stands out as a competitiveness key factor.

This paper presents an approach to the analysis of lubricating oils for Diesel engines, validated on some models of urban buses, as is described along the paper.

The condition monitoring maintenance appeared in the 70-80's to designating a new approach to planned maintenance based on the knowledge of the state of equipment, using condition monitoring techniques, [1].

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Condition monitoring maintenance is the maintenance carried out by means of an evaluation of the equipment state, usually carried out continuously, [2].

According to Pinto [3], the implementation of a condition monitoring system requires investment in equipment, specialized human resources and specific know-how. These systems are supported by computer tools that enable, in an efficient way, the analysis, study, recording and control of the data obtained, and also the establishment of some fault trend curves.

In condition monitoring, a common practice is based on recording the equipment condition, reading data in regular intervals and, since a reading is higher than a pre-set critical level, the equipment monitored is declared faulty and a maintenance intervention is triggered. However, surprisingly, both in practice and theory, little attention has been paid to whether or not the critical level and the monitoring interval are set in a cost effective way, [4].

Maintenance, in general, and the condition monitoring, in particular, aims to combine the increase of reliability with the lower costs possible, being these direct or indirect. In this type of maintenance, the ecological variables may overlap with the remaining ones. However, conventional indicators are not always fully compatible with environmental indicators, [5].

According to Ferreira [6], to increase availability implies reducing the number of breakdowns, repair and inspection times: It follows that it is not enough to have reliable equipment to obtain high availability rates - it is also necessary to ensure maximum speed in repair, maintenance and inspection operations.

According to Ahmad and Kamaruddin [7], the issue that most of the Condition Based Maintenance (CBM) studies focused on is the deterioration modelling process. Although deterioration modelling is one of the important processes in the CBM programme, the follow-up action toward maintenance decision-making is just very important.

An integrating approach of the Life Cycle of a Physical asset can be seen in Farinha (2018), namely including management standards, like ISO 55000X interconnected with some econometric models to evaluate their Life Cycle Costs [8].

There are several approaches to forecast the evolution of oil degradation. Newell discusses an approach based on trend analysis to maximize oil change intervals. This author considers the following common oil analysis tests and procedures: viscosity; total acid number (TAN); total base number (TBN); water content; specific gravity; particle count (visual method); spectrometric analysis; ferrographic analysis, [9]. Macián *et al*. present an analytical approach aiming at more accurate wear determination from engine oil samples. The authors ask: “What level of wear rate is normal or abnormal for the engine studied?” To answer the question, they propose a comparative parameter Z; it takes into account both the deviation from the engine reference wear rate and the reference wear rate. The parameter also compares the current situation to the behavior of a larger population, such as all engines of the same model. The authors demonstrate the influence of oil consumption and additions to the contaminant concentration [10].

Vališ, Zák, and Pokora concentrate on metal particles, such as iron (Fe) and lead (Pb), as potential failure indicators. They apply a linear regression model to determine a linear course of Fe and Pb particle generation. They assume a stochastic process with time dependence. The authors conclude by the importance of time series comparisons: Auto Regression Integrating Moving Average (ARIMA); Auto Regression Moving Average (ARMA) methods [11]. Changsong *et al*. present a study based on 50 oil samples collected and analyzed in sequence covering 250 motor hours. The results show that maintenance intervals can be longer and, at the same time, the cost-effectiveness maintenance ratio can be increased [12].

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Macián *et al*. say that Low Viscosity Engine oils (LVO) are considered key contributors for improving fuel economy in Internal Combustion Engines (ICE). Attending that the use of LVO could imply a variation in tribological states found in ICE; this work's aim was to test LVO in real fleet, with emphasis on engine wear and oil Key Performance Indicators (KPI). This test comprised 39 buses, two engine technologies and four different lubricants [13].

Macián shows the results of a comparative fleet test, which the main objective was to measure the influence of Low Viscosity Oils (LVO) over the fuel consumption and CO_2 emissions of urban buses. To perform this test, 39 urban buses, classified into candidate and reference groups depending on the engine oil viscosity, covered a 60,000 km mileage corresponding to two rounds of standard Oil Drain Interval (ODI). In the same way, for 9 buses of the 39 buses, the effect of differential LVO over fuel consumption and their interaction with engine LVO was assessed during the second ODI. Test results confirm that the use of LVO could reduce fuel consumption, hence CO_2 emissions. However, special attention should be taken prior to its implementation in a fleet, particularly if the vehicles powered by engines with high mechanical and thermal stresses during vehicle operation because this could lead to friction loss increase, loss of the potential fuel consumption reduction of LVO and, in the worst scenario, higher rates of engine wear [14].

Results have shown that LVO presented an excellent performance along the ODI, even improving some characteristics of the baseline oils with higher viscosity values. Those results have shown that oil degradation is more dependent on engine technology, but in any case presented a penalization in terms of ODI reduction, a key indicator for end-users related to maintenance costs. In the case of Compressed Natural Gas engines, higher oil degradation in terms of oil oxidation and nitration was observed [15].

The increasingly stringent emissions regulations and the climatic change as consequence of greenhouse gases emissions have moved the research interest towards the optimization of the internal combustion engine. Hence, the reduction of the energy losses of the engine sub-systems like friction and parasitic energy consumption are of especial interest. Tormos *et al*. [16] present a model to determine the friction losses and the engine accessories energy consumption is developed based on parameters obtained in standard test benches. A description of the models to estimate friction in the piston assembly, bearings and valve train, and energy consumption of the coolant, oil and fuel pump is provided. Finally, a brief application to demonstrate the model potential in diagnosis and predictive applications is discussed [16].

Although not the topic of this paper, multivariate statistics is also useful, because oil analysis involves several variables; an approach like this may help diagnosis of the health of diesel engines. We refer some additional references: [17], [18] and [19].

2. CONDITION MONITORING WITH PREDICTION THROUGH OIL ANALYSIS

The main physical feature of lubricating oil is viscosity and its variation with temperature, given by the viscosity index and the density.

In recent years, there has been a demand for high-performance engine lubricants, especially in the aerospace and automotive industries. This has led to the development of synthetic lubricants which can be maintained at high temperatures without decomposition and have a low risk of combustion.

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The synthetic oils are produced using highly refined processes and sophisticated formulations. They are derived from synthetic compounds based on PAO (polyolefin, polyester, polyglycol), non-synthetic PAO, esters, alkylated naphthalene and alkylated benzene. The use of synthetic oils has become more important in areas where the use of mineral oils does not meet the required needs.

Lubricating oils can cause serious environmental problems if they are discharged indiscriminately, polluting rivers and groundwater. The improper burning of oil adds oxides and toxic gases to the atmosphere. Accordingly, the manufacturers of additives and lubricating oils have been developing products with a longer life, as this tends to reduce oil discharges along the equipment life cycle.

A key feature of lubricants is their behavior with increasing temperature. They are not used at room temperature; the temperature and pressure are often high. The oils undergo change when the temperature increases, and their degradation under operating conditions is a problem involving significant economic losses. To report certain special properties of the oil, or to improve the existing ones, especially when the lubricant is subjected to severe working conditions, chemicals are added (additives). The degradation of a lubricant is not an instantaneous process – the loss of its physicochemical properties and contamination are progressive over time and with the use of equipment along its lifetime. Lubricant degradation is affected by [20]: oxidation; viscosity variation; contamination; loss of additives (anti-corrosion, anti-wear, dispersing agents, etc.).

Today's high-performance lubricants do more than simply reduce friction and wear: they control the formation of deposits, control airborne contaminants, protect against corrosion, have a cleaning function, and maintain the proper operating temperature.

2.1 Oil analysis

Under certain conditions, a lubricant can deteriorate and no longer fulfill its intended function. It is generally a function of the length of service, system temperature, environmental conditions or the stress that it is suffering and can often be traced to the presence of dirt or water, acidity, insufficient flow, or inappropriate levels of viscosity. Any of these can cause lubricated components to malfunction. Even when the lubrication system is well designed and maintained, breakdowns can occur in the component, resulting in the deterioration of the lubricant. The deterioration can be chemical or physical, generated internally by the lubricant or by external phenomena. Physical deterioration, often called contamination, materializes as foreign matter in the lubricant, such as water, foundry sand, weld slag particles, metal shavings, dust and abrasive wear particles.

Lubricant analysis is regularly performed in some industries [21]. It involves four basic steps:

1) Obtaining a sample
    - Collection of a representative sample of a lubricant, observing certain precautions such as: using clean and dry containers; taking extreme care during collection to prevent external contamination; taking samples at operating temperatures.
2) Identifying a relevant sample.
3) Performing physical-chemical analysis:
    - Degree of physical and chemical deterioration, i.e., the degree of contamination and degradation, can be evaluated using a set of standard and specialized tests, such as: measuring certain properties and comparing these with a baseline value.

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- Analyses can measure several properties of the lubricant and evaluate their degradation. These include: antifreeze; appearance; fuel; content water; soot; nitration; oxidation; sulfation; viscosity; viscosity index; total base number; wear metals (Al content, Cr, Fe, Mo, Na, Ni, Pb, Si, Sn, V); particles.

4) Interpreting results – diagnosis.
5) Validating diagnosis:
   - Frequency with which each lubricant ought to be checked depends on various operational factors such as: importance of the equipment; total time of service; scale of production; security; time to failure after detection.

In this section the analysis of service lubricants is addressed, with the monitoring of the evolution of the degradation of the Diesel oils of one the bus fleet; this will have three well-defined phases:

1) In a first phase they will be selected the vehicles that will be the target of analysis and monitoring in the evolution of the degradation of the oils; this monitoring will be done through the periodic collection of samples of the oils of the selected vehicles and sending to a proper place for their analysis;
2) In a second phase, an in-depth study of the results obtained in the analyses, as well as of the prediction algorithms to be used will be carried out;
3) In the third and final phase, an analysis will be made of planned maintenance plans with a view to their improvement. This shall take into account the results obtained in monitoring the evolution of oil degradation; this phase will also serve to present proposals for the improvement of planned maintenance schedules and the reduction of costs that come from it.

This monitoring was done through periodic collection of oil samples from the various vehicles selected and, since there was a small number of samples collected during the period in which this monitoring was developed, it was felt the need to use data from older samples belonging to the same homogeneous group.

These samples were sent to a laboratory based in a European Country, with all the characteristics of the vehicle and the oil, such as:

- Number vehicle;
- Brand;
- Model;
- Type of car;
- Organ – Motor;
- Equipment Km;
- Km of the oil;
- Sample date;
- Date of submission of the sample.

Subsequently, the reports of the results obtained from the various analyses carried out on the samples collected were received (Figure 1).

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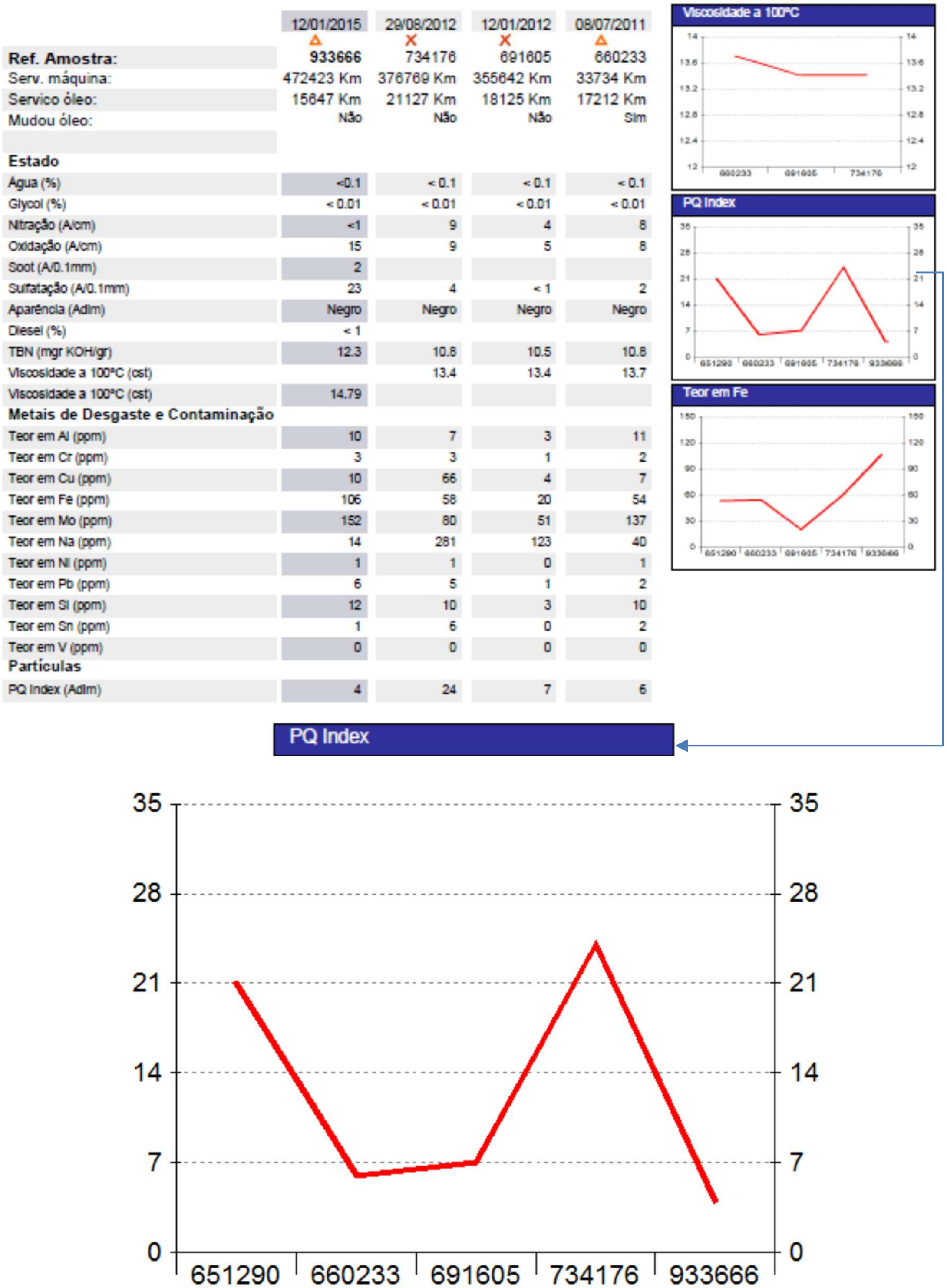

	12/01/2015	29/08/2012	12/01/2012	08/07/2011
Ref. Amostra:	933666	734176	691605	660233
Serv. máquina:	472423 Km	376769 Km	355642 Km	33734 Km
Servico óleo:	15647 Km	21127 Km	18125 Km	17212 Km
Mudou óleo:	Não	Não	Não	Sim
Estado				
Água (%)	<0.1	< 0.1	< 0.1	< 0.1
Glycol (%)	< 0.01	< 0.01	< 0.01	< 0.01
Nitração (A/cm)	<1	9	4	8
Oxidação (A/cm)	15	9	5	8
Soot (A/0.1mm)	2			
Sulfatação (A/0.1mm)	23	4	< 1	2
Aparência (Adim)	Negro	Negro	Negro	Negro
Diesel (%)	< 1			
TBN (mgr KOH/gr)	12.3	10.8	10.5	10.8
Viscosidade a 100ºC (cst)		13.4	13.4	13.7
Viscosidade a 100ºC (cst)	14.79			
Metais de Desgaste e Contaminação				
Teor em Al (ppm)	10	7	3	11
Teor em Cr (ppm)	3	3	1	2
Teor em Cu (ppm)	10	66	4	7
Teor em Fe (ppm)	106	58	20	54
Teor em Mo (ppm)	152	80	51	137
Teor em Na (ppm)	14	281	123	40
Teor em Ni (ppm)	1	1	0	1
Teor em Pb (ppm)	6	5	1	2
Teor em Si (ppm)	12	10	3	10
Teor em Sn (ppm)	1	6	0	2
Teor em V (ppm)	0	0	0	0
Particulas				
PQ Index (Adim)	4	24	7	6

Figure 1 - Oil analysis results report - Bus

The data collected was entered into an Excel spreadsheet, in order to create a database where they could be analysed more easily.

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The Figure 2 shows an Excel database example, per vehicle.

Lubricants Analysis

Nº Fleet 287

Equipment Data

Registration: 64-30-XG **Brand:** VOLVO **Model:** B 7 L

Lubricant Data

Lubricant: XXX

√ Normal
Δ To watch
X Danger

Result of Samples

Date		02/01/2008	27/07/2007	10/10/2007	14/02/2008	14/04/2008
Refª sample		396906	373108	383767	403855	414581
Km do Equip.		186 535	102 259	175 819	192 571	198 046
Km do Lubric.		10 000	15 000	15 000	15 000	20 000
State						
Antifreeze (%)	(PE-TA.071)	0.08	0.08	0.08	0.08	0.08
Appearance (adim)	(PE-TA.096)	Negro	Negro	Negro	Negro	Negro
Fuel (%)	(PE-TA.071)	2	2	2	2	2
Water content (%)	(PE-TA.071)	0,1	0.1	0.1	0.1	0.1
Water content (FinachecK) (%)	(PE-5022-AI)					
Soot (%)	(DIN 51452)	2,3	2	2,9	2,5	2,5
Nitration (ABS / cm)	(PE-TA.071)	5	6	4	6	8
Oxidation (ABS / cm)	(PE-TA.071)	2	2	5	2	1
Sulfation (ABS / cm)	(PE-TA.071)	6	6	1	6	8
TBN (mgr KOH / g)	(ASTM D-2896-07a)	10,86	10,2	10,52	10,2	8,9
Viscosity at 100 ° C (cst)	(ASTM D-445-11)	13,3	13,4	14	13,4	13,7
Wear and Contamination Metals						
Content in Al (ppm)	(ASTM D-5185-05 mod.)	3	2	3	2	2
Content in Cr (ppm)	(ASTM D-5185-05 mod.)	1	1	1	1	1
Content in Cu (ppm)	(ASTM D-5185-05 mod.)	2	1	2	1	3
Content in Fe (ppm)	(ASTM D-5185-05 mod.)	28	24	35	31	56
Content in Mo (ppm)	(ASTM D-5185-05 mod.)	3	2	2	2	2
Content in Na (ppm)	(ASTM D-5185-05 mod.)	14	0	9	3	9
Content in Ni (ppm)	(ASTM D-5185-05 mod.)	1	0	0	0	1
Content in Pb (ppm)	(ASTM D-5185-05 mod.)	1	4	2	3	3
Content in Si (ppm)	(ASTM D-5185-05 mod.)	10	14	12	6	10
Content in Sn (ppm)	(ASTM D-5185-05 mod.)	0	0	0	0	1
Content in V (ppm)	(ASTM D-5185-05 mod.)	0	0	0	0	0
Particles						
PQ Index (Adim)	(PE-5024-AI)	16	25	9	6	16
Diagnosis						
Sample Diagnosis		X	Δ	Δ	Δ	Δ

Figure 2 - Database in Excel

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The data entered are no more than the various results obtained when analysing the variables that characterize the lubricants. In this phase, the variables were analysed using the method presented in Section 4, which allows monitoring the evolution of the degradation of the oils.

All variables were studied; however, this paper will focus only on those that were considered most important for the monitoring of the degradation of oils, which are:

- Soot (Carbon Matter);
- Viscosity;
- TBN;
- Wear and Contamination Metals;
- Particles.

Therefore, for the study of the variables used as reference, the limits made available by the laboratory were used, as can be seen in Table 1.

Table 1 - Limits for the various parameters

Characteristics of the oil		**Limits (X > Danger)**
Antifreeze (%)	(PE-TA.071)	0,08
Appearance (adim)	(PE-TA.096)	
Fuel (%)	(PE-TA.071)	4,0
Water content (%)	(PE-TA.071)	0,2
Water content (FinachecK) (%)	(PE-5022-Al)	0,2
Soot (%)	(DIN 51452)	1,5
Nitration (ABS / cm)	(PE-TA.071)	15
Oxidation (ABS / cm)	(PE-TA.071)	15
Sulfation (ABS / cm)	(PE-TA.071)	20
TBN (mgr KOH / g)	(ASTM D-2896-07a)	30
Viscosity at 100 ° C (cst)	(ASTM D-445-11)	15
Wear and Contamination Metals		**Limits**
Content in Al (ppm)	(ASTM D-5185-05 mod.)	20
Content in Cr (ppm)	(ASTM D-5185-05 mod.)	10
Content in Cu (ppm)	(ASTM D-5185-05 mod.)	35
Content in Fe (ppm)	(ASTM D-5185-05 mod.)	90
Content in Mo (ppm)	(ASTM D-5185-05 mod.)	20
Content in Na (ppm)	(ASTM D-5185-05 mod.)	40
Content in Ni (ppm)	(ASTM D-5185-05 mod.)	20
Content in Pb (ppm)	(ASTM D-5185-05 mod.)	40
Content in Si (ppm)	(ASTM D-5185-05 mod.)	20
Content in Sn (ppm)	(ASTM D-5185-05 mod.)	15
Content in V (ppm)	(ASTM D-5185-05 mod.)	00
Particles		**Limits**
PQ Index (Adim)	(PE-5024-Al)	110

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One the variables considered most important and to which the necessary study was given was the Iron content (ppm). This allowed us to draw several conclusions, which are described later, on the state of degradation of the oil and the equipment.

2.2 Oil analysis changings through prediction

In first step, it was applied the exponential smoothing method to the iron content (Fe) to determine the evolution of its degradation, as can be seen in Table 2 and Figure 3. The table and graph show a clear degradation in the iron content of the analyzed oils. Obviously, the prediction of the next values will involve increased degradation. When this variable has values like those shown in the table, the oil must be replaced, because the equipment is at a high risk level.

The main formula for exponential smoothing is given by:

$$S_{t+1} = \beta.x_t + (1-\beta)S_t \Leftrightarrow S_{t+1} = \beta\sum_{i=0}^{t}(1-\beta)^i x_{t-i} \tag{1}$$

$$0 \le \beta \le 1$$

where:

- S_{t+1} Is the forecast for the next time;
- x_t Is the real value recorded in the present time;
- S_t Is the forecasted value for the present time;
- β Is the smoothing parameter.

Table 2 - Application of exponential smoothing - Fe (ppm) content

Fe Content (ppm)				
Period km	**Observed value**	**Pred. with β=0.1**	**Pred. with β=0.5**	**Pred. with β=0.9**
2 451	19			
5 214	53	19.00	19.00	19.00
10 115	22	22.40	36.00	49.60
12 403	14	22.36	29.00	24.76
17 212	54	21.52	21.50	15.08
22 183	141	24.77	37.75	50.11
27 682	28	36.39	89.38	131.91
30 965	77	35.55	58.69	38.39
35 965		39.70	67.84	73.14

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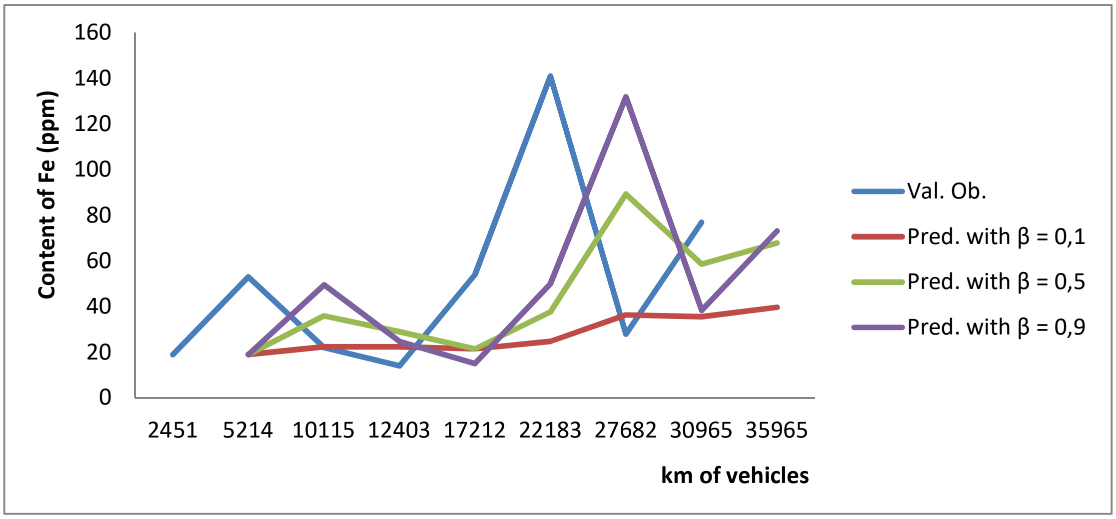

Figure 3 – Graph of exponential smoothing – Fe (ppm) content

In the second part of the development of algorithms for our model, we analyzed the data using the t-Student distribution, $n \leq 30$, [22].

$$\mu = \overline{X} + t_{\alpha} \times \frac{S}{\sqrt{n}} \tag{2}$$

Where,

μ	Is a fixed value used for comparison with the sample mean;
$\overline{X}$	Is the average sample;
t_{α}	Corresponds to the critical T;
S	Is the sample standard deviation;
n	Is the sample size.

Where t_{α} corresponds to the critical t of a tail, considering the desired confidence interval, and the degrees of freedom n-1.

Next, we followed up on the evolution of the degradation of this variable using the t-student distribution. The objective was to estimate the average value of iron (Fe). As Table 3 shows, the average Fe content was 51 (ppm). This is above the upper normal limits, suggesting a high level of degradation. Note that through additional methods, like the t-student test, it is possible to calculate other important data, such as the sample mean, sample standard deviation, and upper parameter limit for several confidence intervals.

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Table 3 – Application of t-student test to iron content - Fe (ppm)

Content Fe (ppm) t-Student					
	α = 0.001	**α = 0.01**	**α = 0.05**	**α = 0.1**	**α=0.2**
Average (sample) $\overline{X}$	51.00	51.00	51.00	51.00	51.00
Standard deviation (sample) S	42,35	42,35	42,35	42,35	42,35
Critical *t*	4.79	3.00	1.89	1.41	0.90
Standard deviation (population) σ	46.27	34.83	24.63	19.19	12.60
Population Average (μ_o)	51 + 46.2	51 + 34.8	51 + 24.6	51 + 19.1	51 + 12.6
Upper limit	97.27	85.83	75.63	70.19	63.60

Lastly, we used bilateral tests of hypotheses for the value of μ:

H_0: $\mu=\mu_0$

H_1: $\mu\neq\mu_0$

μ is considered a random variable whose distribution for small samples ($n < 30$) is given by:

$$t = \frac{\overline{X} - \mu_0}{\frac{S}{\sqrt{n}}} \tag{3}$$

In general, σ (standard deviation of the population) is unknown. The process is the following:

- A one-tailed test uses one threshold value (associated with the chosen significance level) and rejects the hypothesis H_0 - where $T > T\ critical$ - when the value of the modulus calculated for the t statistic exceeds the critical value.

Finally, they were estimated the population average of the iron for the following significance levels: 0.001; 0.01; 0.05; 0.1; 0.2. As Table 4 shows, with a value of 80 (ppm) and a confidence interval of 99%, the hypothesis H_0 is not rejected. But with a 90% confidence interval, H_0 will be rejected because the value of t (1.59) is higher than the value of the confidence interval (1.41). Furthermore, with a confidence interval of 80% (0.90) and a sample average of 51.00, the average value is 37.59.

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Table 4 – Application of t-student test to iron content (Fe)

Hypothesis Test					
μ_0 (population average)	***Calculated t***	***Table t α= 0.001***	***Table t α= 0.05***	***Table t α= 0.1***	***Table t α= 0.2***
25.00	*1.23*	*4.79*	*1.89*	*1.41*	*0.90*
35.00	*0.76*	*4.79*	*1.89*	*1.41*	*0.90*
45.00	*0.28*	*4.79*	*1.89*	*1.41*	*0.90*
50.00	*0.05*	*4.79*	*1.89*	*1.41*	*0.90*
65.00	*-0.66*	*4.79*	*1.89*	*1.41*	*0.90*
75.00	*-1.13*	*4.79*	*1.89*	*1.41*	*0.90*
80.00	*-1.59*	*4.79*	*1.89*	*1.41*	*0.90*
	$\mu 0$	*20.64*	*22.64*	*29.82*	*37.59*

3. DISCUSSION

With this condition monitoring model several variables can be evaluated, that can help to understand the evolution of the degradation' state of the oils. The models exemplified here were applied in three ways:

1) Individually, to all vehicles (all parameters);
2) Homogeneous groups of different vehicles (all parameters);
3) To the group of vehicles that use biodiesel as fuel (all parameters).

The exponential smoothing was applied to the iron content (Fe) variable for a bus number XX_3 to determine the evolution of its degradation. When this variable has high values, the equipment is at a high risk level, and the oil must be changed. The second model applied to monitor the degradation of the iron content was based on the t-student distribution: it estimates the average of iron content (*Fe*) - the average content is 99,80 (ppm).

It is also possible to calculate more information such as the sample mean, the sample standard deviation and the upper limit of the parameter to determine the confidence intervals. If the value of 150 (ppm) is found in the iron content variable, with a 99% confidence interval, the hypothesis H_0 is not rejected. But, if the confidence level is 90%, H_0 is rejected. The value of *t* (2,35) cannot be greater than the value of the confidence interval (1,53).

If the value of *t* is used from the t-student table with 80% confidence interval (0,90) and a sample mean of 99.80, a mean value for a population of 70,48 is obtained.

Because the oil itself and the enormous influence that it has in the Diesel engines condition, the accompaniment of its degradation permits to maximize the bus availability itself and the bus fleet in general.

The paper demonstrates that using condition monitoring maintenance, the intervals of the interventions can be increased and, consequently increased the bus fleet availability, reducing the maintenance costs.

Table 5 shows the data about the company under study, such as the number of buses that constitutes the fleet, their availability, the need of buses for production, the number of buses

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under maintenance and the number of buses that correspond to the reserve fleet, based on a systematic preventive maintenance policy.

Figure 4 (radar map) shows the Availability *versus* Production Requirement (buses necessary to carry out the careers) of the company during a year.

Table 5 – Availability versus Need for buses – Systematic preventive maintenance

Months	Bus Fleet	Availability	Need	Maintenance	Reserve Fleet
January	115	107	90	18	7
February	115	104	90	21	4
March	115	105	90	19	6
April	115	106	90	18	7
May	115	107	90	18	7
June	115	106	90	19	6
July	115	102	90	22	3
August	115	103	90	22	3
September	115	106	90	19	6
October	115	107	90	18	7
November	115	109	90	16	9
December	115	106	90	18	7

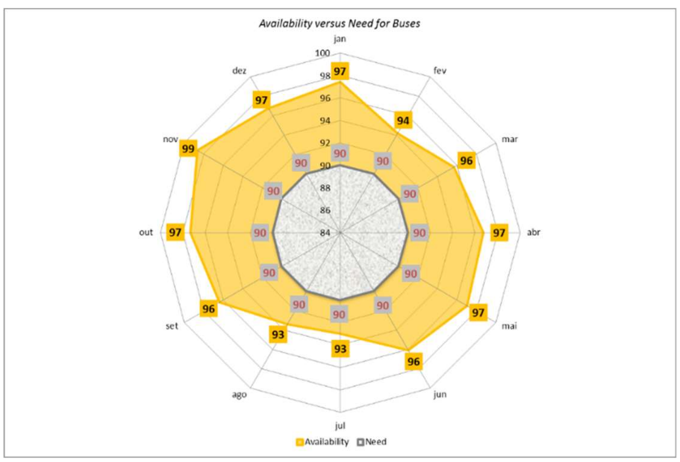

Figure 4 – Availability versus Need for buses – Systematic Preventive Maintenance

4. CONCLUSIONS

The implementation of a condition monitoring based maintenance policy may maximize the physical asset availability, reduce the costs of maintenance, reduce overhead costs and provide an additional guarantee of reliability.

The paper shows how some variables, such as soot and iron content, indicate the condition of Diesel engines. The analysis can be extended to include other variables.

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The paper demonstrates that monitoring the condition of oil can increase the availability of equipment and improve fault prevention by allowing early intervention in degradation. It also demonstrates that the implementation of a condition monitoring based maintenance policy, using oil analysis has huge advantages for public transport companies, including lower downtime, higher availability and, consequently, better service to users.

Additionally, this kind of maintenance policy contributes to the rationalization of the size of a reserve fleet.

Finally, the methodology can be used for many other types of physical assets.

REFERENCES

[1] Cabral, J. S. (2006): “Organização e Gestão da Manutenção”. Lisboa: 6ª Edição. Lidel – Edições Técnicas Lda. ISBN: 978-972-757-440-7.

[2] Assis, R. (1997): “Manutenção Centrada na Fiabilidade”. Lisboa: Lidel – Edições Técnicas Lda. 978-972-757-037-9.

[3] Pinto, C. V. (2002): “Organização e Gestão da Manutenção”, Lisboa: 2ª Edição, Monitor – Projeto e Edições, Lda. ISBN: 978-972-941-339-1.

[4] W. Wang. (2000): “A Model to Determine the Optimal Critical Leveland the Monitoring in Condition Based Maintenance”, International Journal of Production Research, Vol. 38, N. 6, pp, 1425-1436.

[5] Simões, A. S. (2011): “Manutenção Condicionada às Emissões Poluentes em Autocarros Urbanos, Utilizando Modelos de Previsão de Degradação Baseados nas Tecnologias dos Veículos e nas Condições de Exploração”, Tese de doutoramento. Instituto Superior Técnico.

[6] Ferreira, L. A. (1998): “Uma Introdução à Manutenção. Porto”. Publindústria. ISBN 972-957-94-4-X.

[7] Ahmad, R; Kamaruddin, S. (2012): “An overview of time-based and condition-based maintenance in industrial application”, Computers & Industrial Engineering, Vol. 63, N. 1, pp. 135–149.

[8] Farinha, J. T. (2018): “Asset Maintenance Engineering Methodologies”. CRC Press; 1st edition (May 29, 2018). English. Printed in USA. ISBN-10: 1138035890. ISBN-13: 978-113-803-589-8.

[9] Newell, G. E., (1999): “Oil analysis cost-effective machine condition monitoring technique”. Industrial Lubrication and Tribology. Vol. 51, N. 3, pp. 119–124. MCB University Press. ISSN 0036-8792.

[10] Macián, V; Tormos, B; Olmeda, P; Montoro, L., (2003): “Analytical approach to wear rate determination for internal combustion engine condition monitoring based on oil analysis”. Tribology International, Elsevier Science Ltd. Vol. 36, pp. 771–776. doi:10.1016/S0301-679X(03)00060-4.

[11] Vališ, D.; Zák, L.; Pokora, O., (2015): “Failure prediction of diesel engine based on occurrence of selected wear particles in oil”. Engineering Failure Analysis Vol. 56, pp. 501–511. http://dx.doi.org/10.1016/j.engfailanal.2014.11.020.

[12] Z. Changsong; Liu, P.; Liu, Y.; Zhang, Z. (2018): “Oil-based maintenance interval optimization for power-shift steering Transmission”. Advances in Mechanical Engineering, Vol. 10, N. 2, pp. 1–8. DOI: 10.1177/1687814018760921.

[13] Macián, V; Tormos, B; Ruíz, S.; Miró, G. (2016): "Low viscosity engine oils: Study of wear effects and oil key parameters in a heavy duty engine fleet test". Tribology International, Vol. 94, N. 1, pp. 240–248.
[14] Macián, V; Tormos, B; Miró, G.; Pérez T. (2016): "Assessment of low-viscosity oil performance and degradation in a heavy duty engine real-world fleet test". Proc IMechE Part J: Journal Engineering Tribology. Vol. 230, N. 6, pp. 729–74. DOI: 10.1177/1350650115619612.
[15] Macián, V; Tormos, B; Ruíz, S.; Ramírez, L. (2015): "Potential of low viscosity oils to reduce CO2 emissions and fuel consumption of urban buses fleets". Transportation Research Part D - Transport and Environment, Elsevier Ltd.. Vol. 39, pp. 76–88. http://dx.doi.org/10.1016/j.trd.2015.06.006.
[16] Tormos, B; Martín, J.; Carreño, R.; Ramírez, L. (2018): "A general model to evaluate mechanical losses and auxiliary energy consumption in reciprocating internal combustion engines". Tribology International, Elsevier Ltd.. Vol. 123, pp. 161–179. DOI: 10.1016/j.triboint.2018.03.007.
[17] Sen, P. K. (1986): "Review: Contemporary Textbooks on Multivariate Statistical Analysis: A Panoramic Appraisal and Critique". Journal of the American Statistical Association. Vol. 81, N. 394, pp. 560-564. DOI: 10.2307/2289251.
[18] Schervish, M. J. (1987): "A Review of Multivariate Analysis". Statist. Sci. Vol. 2, N. 4, pp. 396-413. doi:10.1214/ss/1177013111. https://projecteuclid.org/euclid.ss/1177013111
[19] Jun, H. B.; Kiritsis, D.; Gambera, M.; Xirouchakis, P. (2006): "Predictive Algorithm to Determine the Suitable Time to Change Automotive Engine Oil". Computers & Industrial Engineering. Vol. 51, N. 4, pp. 671-683. https://doi.org/10.1016/j.cie.2006.06.017.
[20] Seabra, J.; Graça, B. (1996): "Análise de óleos e massas lubrificantes em Serviço". Actas do Quinto Congresso Nacional de Manutenção Industrial – APMI, Figueira da Foz, 1996.
[21] Gresham, R. M.; Totten, G. E. (2008): "Lubrication and Maintenance of Industrial Machinery", Best Practices and Reliability. Publisher: CRC Press. ISBN-10: 1420089358. ISBN-13: 978-142-008-935-6.
[22] André, J. C. S., (2008): "Probabilidades e Estatística para Engenharia", Lisboa: 1ª Edição, Lidel – Edições Técnicas Lda. ISBN: 978-989-752-112-6.