João RODRIGUES
Inês COSTA
J. TORRES FARINHA
Mateus MENDES
Luís MARGALHO

PREDICTING MOTOR OIL CONDITION USING ARTIFICIAL NEURAL NETWORKS AND PRINCIPAL COMPONENT ANALYSIS

PROGNOZOWANIE STANU OLEJU SILNIKOWEGO ZA POMOCĄ SZTUCZNYCH SIECI NEURONOWYCH I ANALIZY SKŁADOWYCH GŁÓWNYCH

The safety and performance of engines such as Diesel, gas or even wind turbines depends on the quality and condition of the lubricant oil. Assessment of engine oil condition is done based on more than twenty variables that have, individually, variations that depend on the engines' behaviour, type and other factors. The present paper describes a model to automatically classify the oil condition, using Artificial Neural Networks and Principal Component Analysis. The study was done using data obtained from two passenger bus companies in a country of Southern Europe. The results show the importance of each variable monitored for determining the ideal time to change oil. In many cases, it may be possible to enlarge intervals between maintenance interventions, while in other cases the oil passed the ideal change point.

***Keywords**: condition monitoring, oil analysis, multivariate analysis, predictive maintenance.*

Bezpieczeństwo i wydajność silników takich, jak silniki Diesla czy gazowe, a nawet turbiny wiatrowe, zależą od jakości i stanu oleju smarowego. Stanu oleju silnikowego ocenia się na podstawie ponad dwudziestu zmiennych, z których każda ulega wahaniom w zależności od typu i zachowania silnika oraz innych czynników. W niniejszym artykule opisano model, który pozwala na automatyczną klasyfikację stanu oleju, z wykorzystaniem sztucznych sieci neuronowych i analizy składowych głównych. Badania przeprowadzono na podstawie danych uzyskanych od dwóch przewoźników pasażerskich działających na terenie jednego z krajów położonych na południu Europy. Wyniki pokazują, że każda z monitorowanych zmiennych ma znaczenie dla określenia idealnego czasu na wymianę oleju. Podczas gdy w wielu przypadkach w badanych przedsiębiorstwach możliwe było zwiększenie odstępów czasowych między działaniami konserwacyjnymi, w innych, idealny moment wymiany oleju został przekroczony.

***Słowa kluczowe**: monitorowanie stanu, analiza oleju, analiza wielowymiarowa, konserwacja predykcyjna.*

1. Introduction

Condition monitoring of engines' oil is a strategic area in the maintenance management field. Replacing the oil too early represents unnecessary unavailability, as well a financial and environmental costs which could be spared. Replacing it too late can impair the oil's ability to protect the engine, therefore increasing the chances of damage and premature ageing of the engine, or even the risk of causing accidents which can endanger people, equipments or vehicles in urban environments. The use of modern tools from data mining and Artificial Intelligence (AI) can contribute to help make the right decision at the right time, thus protecting the environment, the companies' profits and the safety of people and property.

The present paper discusses a methodology to create models to facilitate the process of oil analysis, tested with a dataset for oil of Diesel engines, from urban passenger buses. Preliminary work was already done [14], using Artificial Neural Networks (ANN). In the present research, the neural models were improved and the results are compared with analysis using multivariate systems, namely Principal Component Analysis (PCA). PCA showed the relevance of each variable is different, and some of the variables may even have a negative impact on the predictive power of the ANN.

Data used for the experiments come from two passenger bus companies. Each company provided a dataset, containing results of laboratory analysis of the oils and their classification, according to human experts of a specialized oil analysis company. Data were mined and neural models were created, for both datasets separated and combined.

The remainder of the paper is organized as follows. Section 2 presents a summary of the state of the art. Section 3 describes the datasets used. Section 4 describes the neural networks. Section 5 describes the analysis performed using multivariate systems. Section 7 presents a comparative and critical analysis of the results obtained. Section 8 highlights the main contributions of the present research. Section 9 presents some conclusions and outlines future work.

2. Literature Review

2.1. Condition monitoring of Diesel engines' oil

Condition monitoring of Diesel engines' oil has been subject to study using different approaches, including machine learning methods. Raposo et al. present a study about condition monitoring based on oil in the Diesel engines of a fleet of urban buses. The study shows

---

(*) Tekst artykułu w polskiej wersji językowej dostępny w elektronicznym wydaniu kwartalnika na stronie ***www.ein.org.pl***

the evolution of oil degradation and develops a predictive mainte-nance policy for oil replacement [13]. The methodology presented by the authors considers only some variables of the oils, showing very interesting results about the P-F curve accompaniment. The P-F curve is the interval between the detection of a Potential failure and the ac-tual Failure— that is, the interval where a maintenance team should intervene to prevent a potential failure from happening.

Gajewski & Valis present a study that focuses on heavy transport systems. The types of oils were obtained from several dozens engines of heavy crawlers. The study uses these data with neural networks, in order to identify the patterns that model the system deterioration [5]. Hongxiang et al. [7] use a feed forward neural network to classify dif-ferent types of oil and their running/not running condition. Parlak et al. [12] use an ANN to predict specific fuel consumption and Diesel engine temperature.

2.2. Online condition monitoring of engine oil

Monitoring the condition or the engine's oil in real time is also a long sought goal. Oil degradation depends on the working time, kilometers driven, the driving speed and habits, type of motor, age of the motor and many other variables which may cause faster or slower degradation. Therefore, for replacement of the oil at the best time, it is necessary to make analysis to determine the state of degradation of the oil. The main problems with laboratory analysis is that they are a laborious process, which requires human intervention. Even though it is only necessary each several km, the idea is to automate the process, thus lowering the costs and reducing the probability of human error.

Accurate online monitoring has two main advantages: i) it reduces downtime necessary to inspect the oil; and ii) it increases chances that the oil will be changed at the best time, not too early and not too late. On the downside, it requires adequate sensors that can be put in the engines, in contact with the oil. The sensors must be robust enough to endure the operating conditions without failing and they must be precise enough to give accurate readings. J. Zhu et al. present a fair review of state of the art sensors and methods for online condition monitoring of engines' oil [18]. The authors classify the sensors in four different groups: electromagnetic, physical, chemical and opti-cal. Electromagnetic sensors measure the dielectric constant of the oil. A second type measures the oil's conductivity. A third type mea-sures magnetic susceptibility. A fourth type measures oil viscosity. As for physical methods, Zhu et al. mention the viscometer, ultra sound, thermal conductivity sensor and ferrography. As for chemical meth-ods, the techniques reviewed include pH measurement and thin-film contaminant monitor. As for optical techniques, they are reflectometry and infrared absorption.

S. Kumar et al. propose a method for condition monitoring oil engine online, based on an optical sensor that transduces oil darkness into electrical resistance [8]. The colour change of the oil is one of the variables that directly correlates to the quality of the oil. Therefore, the authors argue that monitoring the oil colour it is possible to deter-mine the degradation of the oil and change it at the most appropriate time. The method is in part similar to [17], where Yonghui et al., who combine the use of a fibre optic transducer and an inductive sensor. The inductive sensor detects large ferrous and some non-ferrous wear debris, while the optical sensor detects small particles contaming the oil.

El-Hag et al. use features extracted from acousting and radio fre-quency partial discharge signals to monitor oil condition in power transformers [4]. Pulse width, rise time and frequency components are used to train a neural network to assess the level of degradation of the oil. J. Zhu et al. propose a method for condition monitoring wind turbine oil using commercially available sensors to measure oil viscosity and dielectric constant sensors [19]. The sensor readings are calibrated based on the relationship between particle concentration

and oil degradation. X. Zhu et al. propose a method to condition moni-tor oil using a sensor that detects wear debris by measuring the induc-tance change of two planar coils wound around a pair of ferrite cores [20]. The method is in part similar to Du et al.'s approach, which also uses inductive sensors to measure metallic, ferrous and non-ferrous, particles in lubricant oil [3].

2.3. Use of PCA and Artificial Neural Networks in condition monitoring

Principal Component Analysis is one method of multivariate analysis very popular for data mining. It is a statistical procedure to transform data, extract features and determine the most important variables of a dataset. Through PCA analysis, it is therefore possible to predict which variables deserve to be monitored and which vari-ables are candidate to be removed without loosing predictive power. Westerholm and Li use PCA to determine the relationship between fuel parameters and the amount of particles in Diesel motor emis-sions [16]. Capone et al. use PCA to determine the amount of un-burned fuel in lubricating oil [1].

Different Artificial Neural Network architectures have also been used for learning and predicting oil condition. Shaban et al. use a cas-cade of artificial neural networks to predict transformer oil parameters [15]. Niu et al. compare the performance of ANN and Support Vector Machines for predicting motor emissions [11]. Ghobadian et al. use an ANN to model the performance of a diesel engine using waste oil [6]. Li X et al. and Li Y et al. use convolution neural networks to detect gear faults based on different signals, namely sounds produced by the gears [9] and operational parameters [10].

3. Datasets Used

The present research was performed using two datasets, obtained from two different public transportation bus companies, named A and B for that purpose. The datasets contain the results of 21 parameters of the laboratory analysis of the oil, taken from the buses at differ-ent stages. Each sample also contains the bus and the oil mileage. That is a total of 23 parameters which are used as input variables for the present analysis. The 23 parameters are: mileage of the bus, mileage of the oil, amount of antifreeze found in the oil, percentage of fuel, Finacheck water content, sooth, nitration, oxidation, sulfa-tion, TBN, viscosity at $100°C$, Al, Cr, Cu, Fe, Mo, Na, Ni, Pb, Si, Sn, V and PQ. The variables were normalized and used as inputs to the neural networks and PCA analysis. The datasets also contain the decision of the specialized company, marked as 1, 2 or 3. Decision 1 means that the company decided the oil is in good condition and can be maintained for normal bus operation. Decision 2 means the oil is reaching the point where it needs to be replaced. Decision 3 means the oil has passed the point when it should have been replaced and the bus must be immediately stopped for safety reasons. Dataset A con-tains a total of 47 samples, obtained from a number of different buses of company A. Dataset B contains a total of 88 samples, obtained from twenty two different buses, four samples from each bus. For the present study it was not possible to obtain larger datasets—a limita-tion which could not be overcome. Nonetheless, the results obtained for the neural models and PCA were consistent. They were repeated a number of times and they are repeatable in similar circumstances. Many neural models showed good performance and small error in the train and test sets. The ones preferred for analysis were those with better performance in the test set, thus showing the model is general. That shows the results are valid and the method could be scaled up to larger datasets. Since PCA is a factor-analysis method, the adequacy of the datasets for PCA was tested using Kaiser-Meyer-Olkin (KMO) test [2]. KMO test gives a score between 0 and 1, where in general the higher scores mean the dataset contains enough diversity of samples to apply factor analysis. A low score, on the other hand, means there

are high correlations between the variables and the results of the factoring process are unreliable. The KMO test gives a score of 0.35 for dataset A, which is very low, and a score of 0.636 for dataset B, which is acceptable, meaning there is more confidence in the factor analysis results for dataset B.

4. Neural Models

In the present research the neural models used were shallow Feed Forward Neural Networks, with one hidden layer of variable width (number of neurons), and one output layer. The hidden neurons used a sigmoid transfer function, which can be a universal approximation, maintaining the output in the range [0, 1]. The output neuron used a linear transfer function (relu), to allow for a wider amplitude of the

Table 1. R and MSE obtained for different network sizes, with dataset A

Hidden layer size	R (train set)	R (validation set)	R (test set)	R (all dataset)	MSE (all dataset)
1	0.98	0.83	0.78	0.91	0.485
2	0.98	0.76	0.80	0.93	0.234
3	0.99	0.96	0.96	0.98	0.051
4	0.99	0.87	0.88	0.95	0.258
5	0.98	0.91	0.70	0.92	0.229
6	0.95	0.90	0.89	0.92	0.216
7	0.98	0.83	0.98	0.96	0.178
8	0.93	0.83	0.88	0.89	0.291
9	0.92	0.88	0.98	0.91	0.178
10	0.90	0.99	0.91	0.89	0.015

Table 2. Confusion matrices of the errors of the model trained with data from Company A. The model shows two prediction errors for Company A, but 39 errors for Company B

Predicted	Company A			Company B		
3	0	0	**14**	0	0	**4**
2	0	**11**	1	0	**0**	2
1	**20**	1	0	**45**	15	22
Actual	1	2	3	1	2	3

output and facilitate the learning process. The models were created and tested in MatlabTM1. Training was performed using the Levenberg-Marquartd method. The Mean Squared Error (MSE) and correlation factor R were used for performance assessment. Training was performed with 70 % of the samples, validation with 15 % and test with the remainder 15 %. The results of the training process are variable for each experiment. That happens when the initial weights and bias of the neurons are not set for a specific value, or if the samples for the training and validation sets are chosen randomly at each experiment. Therefore, the results of the experiments presented below are selected from a number of runs. During training, the training process was stopped when the error increased in the validation set for two consecutive epochs, and the best model was retained. The output obtained from the neural models is a floating point number. That is desirable, so that it is interpreted as a measure of the quality of the oil: the lowest the value, the better the

quality of the oil. On the other hand, it is also important to map the output to 1, 2 or 3, in order to obtain a model that can be compared to the classification of the human experts, as described in Section 3. So it was mapped in the discrete interval [1, 3] using the following rules: Anything below 1.50 was mapped to 1; Numbers in the interval [1.50, 2.50[were mapped to 2 and everything greater or equal to 2.50 was mapped to 3.

4.1. Model for Company A

In order to get the best possible results, it is important to determine the optimal size of the neural network, so that it is able to abstract and retain as much information as possible without overfitting the training data.

Table 1 shows the R and MSE obtained for a number of neurons between 1 and 10, for dataset A. Many models show good R and MSE. The model with three neurons is one of the best, since it shows a good R for all the dataset and a small MSE. It also shows a good R for the test set, which means it is a good general model, performing well even for data that it has never seen. The number of neurons is small for the number of inputs, but it is probably in line with the size of the dataset, which is also small. The model was trained in three epochs, after which it started to show signs of overfitting and, therefore, further training was rejected.

Table 2 shows the confusion matrices with a summary of the distribution of the errors of the model described above, when applied to both datasets. As the table shows, the predictions of the model for Company A are very close to the desired output. There are only two errors, when the model predicted 2 and the decision was 1 and the model predicted 3 while the company decided 2. In both cases the company was more defensive than the model. It should be mentioned that the decisions made by the company are also prone to human error, so the errors shown are not necessarily problems of the model—they can be because of outliers in the dataset.

When the same model was applied to the data obtained from Company B, there were a total of 39 errors in 88 samples. All the errors apparently happen because Company B was more defensive than the model, showing a very clear trend: the experts rated the oil worse than the model which performed very well for Company A. This proves that Company B replaces the oil, on average, before Company A. That may happen because of different maintenance policies, different motors or different oil brands.

Table 3. R and MSE obtained for different network sizes, with dataset B

Hidden layer size	R (train set)	R (validation set)	R (test set)	R (all dataset)	MSE (all dataset)
1	0.98	0.97	0.86	0.95	0.060
2	0.95	0.93	0.88	0.94	0.110
3	0.99	0.90	0.88	0.96	0.222
4	0.95	0.95	0.83	0.92	0.078
5	0.97	0.86	0.80	0.93	0.161
6	0.86	0.84	0.86	0.86	0.249
7	0.91	0.91	0.91	0.90	0.256
8	0.97	0.89	0.93	0.94	0.144
9	**0.95**	**0.91**	**0.94**	**0.95**	**0.073**
10	0.92	0.89	0.92	0.90	0.184

Table 4. *Confusion matrices of the errors of the model trained with data from Company B. The model shows six prediction errors for Company B, but thirty three errors for Company A*

Predicted	Company A			Company B		
3	16	12	**14**	0	0	**26**
2	4	**0**	0	4	**15**	2
1	**0**	0	1	**41**	0	0
Actual	1	2	3	1	2	3

4.2. Model for Company B

Table 3 shows the R and MSE obtained from a number of neurons between 1 and 10, for models trained with dataset B. The network with one neuron in the hidden layer shows the lowest MSE. However, it also shows a poor R in the test set, compared to the train and validation sets, meaning the model is a bit overfitted. The model with nine neurons in the hidden layer is better, considering that it shows a high R for all dataset, a high R for the test set and a small MSE. That shows the model is more general for the specific problem being addressed. The best performance for the test and validation sets was obtained at epoch four, and after that the model starts to overfit the data.

Table 4 shows the confusion matrices for the model, applied to datasets B and A. On dataset B, there are six errors of the model, compared to the decision of the company. In four situations the model predicted 2, while the company decided 1. So, the model was more defensive, proposing the bus to replace the oil, while the company decided it was good to circulate. In two cases, the model predicted 1 and the company decided 2.

When the same model was applied to data from Company A, there was a total of thirty three errors. In one situation the company was more defensive: one time the model predicted 1 and the company, apparently, decided to stop the bus. In thirty two situations the model was more defensive: sixteen times the model predicted the bus should be taken out of circulation and the company decided the oil was good, twelve times the model predicted the bus should be taken out of circulation and the company just decided to replace the oil, and four times the model predicted the oil should be replaced and the company decided it was good. The results of this confusion matrix are according to the one shown in Table 2: the companies follow different policies, and Company B replaces the oil much earlier than Company A.

5. Principal Component Analysis

5.1. Introduction

PCA is a statistical procedure used to map a set of correlated variables into a new set of uncorrelated variables, called principal components. The principal components are calculated by decreasing order of importance. The first component is the most important, the last is the less important explanatory variable. Each principal component identified is a linear combination of all the original variables. PCA was applied to the datasets presented above, in order to understand the companies' policies, the state of the oils when the samples were collected for chemical analysis, as well as to determine which variables are more important to measure for correct assessment of the situation of the oil. The PCA experiments and analysis were performed using R Studio software.

5.2. Loadings for each variable of the dataset

Table 5 shows results of the PCA analysis for datasets A and B. As the table shows, Si, Fe, Al and Cr contents are the four most important variables, with loadings above 0.7, for dataset A.

For dataset B, Fe, Soot and Cr are the top three variables, and the only ones with score above 0.7. Five of the top ten variables are related to oil status and five are related to wear and contamination.

5.3. Company A

For Company A, the most important components are polluting metallic agents, which are generated by motor wear: slip wear, wear due to friction, wear due to metal fatigue, and wear due to cutting. This means the bus motors suffer a lot of wearing, being advisable the use of additives to reduce friction, oil leaks and even fumes. The use of the right additives might also increase motor expected life.

Table 6 shows the calculated percentage of deterioration of the oil, for each oil sample, as well as the average deterioration. The percentage of deterioration was obtained multiplying the PCA loadings by the normalized value of each variable. So a kind of weighted average is obtained and then compared to the reference values obtained from the oil datasheet.

As the table shows, four different oils are already well beyond their expected useful life, based on manufacturer recommendations. More than 41 % of the samples have passed 60 % degradation. Another relevant aspect is that there is a large variability between samples. The standard deviation in the dataset is 0.312. In general, Company A apparently has a poor maintenance policy. On one hand, the motors suffer a lot of wearing when the oils are still used beyond their reference limits. That can damage the motors and reduce their useful life. On the other hand, some oils may be changed while they are still good, causing unnecessary financial and environmental costs. In two

Table 5. *Most important variables, according to PCA analysis, for datasets A and B. The ten first variables that are in both datasets are highlighted in bold*

Order of Relevance	Variable	Loading	Variable	Loading
1	**Si Content**	0.872	**Fe Content**	0.889
2	**Fe Content**	0.864	**Soot**	0.835
3	**Al Content**	0.789	**Cr Content**	0.781
4	**Cr Content**	0.729	Viscosity at 100°C	0.689
5	**Sn Content**	0.668	**Sn Content**	0.682
6	**PQ Index**	0.551	**Cu Content**	0.611
7	Ni Content	0.425	Pb Content	0.571
8	**Soot**	0.441	**Sulfation**	0.507
9	**Oxidation**	0.412	Nitration	0.496
10	V Content	0.376	**Oxidation**	0.488
11	**Cu Content**	0.282	**Al Content**	0.482
12	**Sulfation**	0.266	**Si Content**	0.423
13	Mo Content	0.166	**PQ Index**	0.32
14	Pb Content	0.134	Na content	0.166
15	Fuel	0.132	Antifreeze	0.162
16	Na Content	0.118	Water Content	0.127
17	Viscosity	0.089	Mo Content	0.072
18	TBN	0.069	V Content	0.02
19	Nitration	-0.003	Ni Content	-0.008
20	Water content	-0.14	Fuel Content	-0.134
21	Antifreeze	-0.142	TBN Content	-0.395

cases the oils are apparently at just 15 % of their useful life when they were replaced, according to the results of the laboratorial analysis.

5.4. Company B

Table 6 shows the percentage of degradation of the oil samples. As the table shows, none of the samples is out of the limits proposed by the manufacturer, showing the oil is in good condition to protect the Diesel engines. In general the dataset is also more homogenous, with most of the variables near the average value. The standard deviation is 0.126, which is much lower than the standard deviation calculated for dataset A.

Table 8 shows tha average deterioration of oil for each of the twenty two buses. The average is always in the range 30 – 59 %. Bus 1814 shows the lowest average of all. Bus 2160 shows the highest average, with 58.65 %, which is already a very high value. In general, however, the buses of company B show a low level of wear, with the five variables related to wearing and contamination within the ten highest principal components because of their importance in oil deterioration.

6. Neural model with reduced dimensionality

6.1. Merging datasets

Since both datasets contain the same 23 input variables and three-levels output variable, they are fit to be merged together, aiming to produce one more general model. However, since data come from different sources, it is important to avoid skewing the results towards the policies of one of the companies, for the previous analysis have shown that the companies follow different policies and the datasets may have outliers. The problem can be seen as the typical problem of imbalanced datasets, which is solved using techniques such as oversampling the less frequent data or undersampling the most frequent data. In the present case, considering the small dimension of the dataset, data from Company A were oversampled choosing randomly additional samples from dataset A after cross validation.

The merged dataset was named AB and it contains a total of 176 samples, 88 from each dataset. The neural models used for experiments with dataset AB all contained seven neurons in the hidden layer. The number of inputs, however, varied: i) one of the experiments was run with all the 21 laboratorial variables and the mileage as inputs for the neural network; and ii) a second experiment was run using as inputs to the neural network just the ten variables highlighted in Table 5.

Table 9 shows the R and MSE obtained for different models. As the table shows, the model with 23 input variables was very good, with a very small MSE. The model with just 12 inputs is also very good, with R 0.94 for all the dataset and 0.84 for the test set. The table shows that reducing the number of variables it was still possible to generate a good neural model, with good R and a small MSE of just 0.15

Table 10 shows the confusion matrices of the errors counted when simulating the two models trained with dataset AB. The model trained with all the 23 inputs generates 13 prediction errors: five for samples of company B and 8 for company A. .

The model trained with just 12 input variables produces a total of 14 prediction errors: 7 for each company. Those results also show that the model trained with just 10+2 variables seems more general than the model trained with all the variables, for it generates the same number of prediction errors for each company. The smaller model, retaining less information, still shows good performance marks and is perhaps the most general, as discussed in Section 7.

Table 6. Percentage of deterioration of the oil for dataset A

Sample	Bus #	% Deterioration	Sample	Bus #	% Deterioration
1	122	31.7	25	267	66.7
2	122	13.6	26	270	32.5
3	203	49.9	27	270	54.2
4	203	18.8	28	270	89.1
5	214	52.1	29	282	54.6
6	214	150.6	30	282	51.7
7	214	35.6	31	283	69.0
8	214	17.6	32	283	70.7
9	219	13.4	33	289	73.1
10	246	79.1	34	289	85.3
11	246	64.0	35	290	49.3
12	247	83.6	36	294	55.8
13	248	73.6	37	294	54.3
14	249	46.5	38	297	62.3
15	251	54.1	39	209	72.5
16	252	69.2	40	209	73.3
17	254	162.1	41	301	31.0
18	259	128.0	42	301	86.8
19	260	88.3	43	301	31.7
20	265	118.3	44	304	66.4
21	266	48.3	45	304	51.6
22	266	45.6	46	304	54.8
23	266	63.7	47	304	35.7
24	267	55.2	**Average**		62.5

Table 7. Percentage of deterioration (Det.) of the oil for dataset B

Sample	Bus #	% Det.	Sample	Bus #	% Det.	Sample	Bus #	% Det.
1	2175	31.1	31	1737	29.1	61	2127	64.6
2	2175	30.4	32	1737	28.4	62	2127	56.7
3	2175	38.7	33	2148	84.2	63	2127	37.4
4	2175	30.0	34	2148	46.1	64	2127	38.8
5	1730	31.9	35	2148	41.0	65	2119	81.9
6	1730	40.5	36	2148	48.7	66	2119	40.0
7	1730	40.1	37	2131	64.1	67	2119	37.1
8	1730	33.0	38	2131	49.1	68	2119	35.3
9	1764	37.3	39	2131	40.8	69	1708	74.8
10	1764	29.3	40	2131	51.9	70	1708	31.2
11	1764	36.4	41	1814	42.8	71	1708	46.2
12	1764	34.2	42	1814	27.7	72	1708	32.2
13	1778	32.9	43	1814	24.5	73	1727	35.5
14	1778	37.7	44	1814	25.0	74	1727	33.9
15	1778	51.0	45	2169	52.8	75	1727	26.8
16	1778	36.3	46	2169	37.2	76	1727	31.0
17	1739	31.6	47	2169	42.6	77	1743	37.4
18	1739	32.5	48	2169	47.2	78	1743	33.3
19	1739	32.4	49	2128	40.3	79	1743	34.7
20	1739	30.6	50	2128	42.6	80	1743	31.0
21	2159	39.8	51	2128	31.8	81	1734	41.3
22	2159	27.1	52	2128	39.6	82	1734	31.4
23	2159	40.0	53	2150	32.7	83	1734	30.7
24	2159	32.3	54	2150	61.4	84	1734	35.9
25	2136	44.2	55	2150	35.8	85	2160	81.1
26	2136	47.1	56	2150	37.2	86	2160	58.7
27	2136	38.4	57	2152	68.1	87	2160	46.5
28	2136	42.0	58	2152	40.4	88	2160	48.3
29	1737	33.5	59	2152	49.1	**Average**		**40.6**
30	1737	32.0	60	2152	37.5			

Table 8. Average deterioration of the oil for each of the twenty two buses for Company B

Bus #	% Deterioration	Bus #	% Deterioration
2175	32.55	1730	36.38
1764	34.30	1778	39.48
1739	31.78	2159	34.80
2136	42.93	1737	30.75
2148	55.00	2131	51.48
1814	30.00	2169	44.95
2128	38.58	2150	41.78
2152	48.78	2127	49.38
2119	48.58	1708	46.10
1727	31.80	1743	34.10
1734	34.83	2160	58.65

Table 10. Confusion matrices of the errors of the model trained with data from AB

# inputs	Predicted	Companies A&B			Company A			Company B		
	3	1	0	**52**	0	0	**25**	1	0	**27**
21+2	2	7	**34**	3	4	**19**	2	3	**15**	1
	1	**77**	1	1	**36**	1	1	**41**	0	0
	3	0	0	**47**	0	0	**24**	0	0	**23**
10+2	2	4	**34**	7	2	**19**	4	2	**15**	3
	1	**81**	1	2	**38**	1	0	**43**	0	2
Actual		1	2	3	1	2	3	1	2	3

Table 9. R and MSE obtained for the neural models trained with dataset AB, using all the input variables and then just 12 selected input variables

# inputs	R (train set)	R (validation set)	R (test set)	R (all dataset)	MSE (all dataset)
21+2	0.97	0.84	0.86	0.93	0.27
10+2	0.96	0.86	0.84	0.94	0.15

7. Discussion and comparison of the results obtained

Using ANN models it was possible to determine companies A and B follow different policies, with Company B being more defensive than Company A. PCA confirmed these results, showing that Company B replaces the oil in the interval from 30 to 59 % of deterioration, while Company A sometimes even passes the limit established by the manufacturer. Using ANN it was

Table 11. Classification of the different samples by the human expert, the Artificial Neural Network, and level of deterioration of the oil according to PCA analysis. Samples where the human expert and the ANN differ are marked in bold.

Human	ANN	Det. (%)	Human	ANN	Det. (%)	Human	ANN	Det. (%)	Human	ANN	Det. (%)
1	1	31.7	1	1	51.6	2	3	37.5	1	1	36.3
1	1	13.6	2	2	54.8	3	3	64.6	1	1	31.6
2	2	49.9	1	1	35.7	3	3	56.7	1	1	32.5
1	1	18.8	1	1	31.7	2	2	37.4	1	1	32.4
1	1	52.1	1	1	13.6	2	2	38.8	1	1	30.6
3	3	150.6	2	2	49.9	3	3	81.9	3	3	39.8
1	1	35.6	1	1	18.8	3	3	40	2	2	27.1
1	1	17.6	1	1	52.1	2	2	37.1	2	2	40
1	1	13.4	3	3	150.6	2	2	35.3	2	2	32.3
3	3	79.1	1	1	35.6	1	1	74.8	3	3	44.2
1	1	64	1	1	17.6	1	1	31.2	3	3	47.1
2	2	83.6	1	1	13.4	1	1	46.2	3	3	38.4
2	2	73.6	3	3	79.1	1	1	32.2	3	3	42
1	1	46.5	1	1	64	**1**	**2**	35.5	1	1	33.5
1	1	54.1	2	2	83.6	1	1	33.9	1	1	32
2	2	69.2	2	2	69.2	1	1	26.8	1	1	29.1
3	3	162.1	3	3	162.1	1	1	31	1	1	28.4
3	3	128	3	3	128	**1**	**2**	37.4	3	3	84.2
3	3	88.3	3	3	88.3	1	1	33.3	3	3	46.1
3	3	118.3	3	3	118.3	1	1	34.7	2	2	41
1	1	48.3	1	1	48.3	1	1	31	3	3	48.7
1	1	45.6	1	1	45.6	**3**	**2**	41.3	3	3	64.1
2	2	63.7	2	2	63.7	1	1	31.4	**3**	**2**	49.1
2	2	55.2	2	2	55.2	1	1	30.7	1	1	40.8
3	3	66.7	3	3	66.7	1	1	35.9	3	3	51.9
1	1	32.5	1	1	32.5	3	3	81.1	1	1	42.8
1	1	54.2	1	1	54.2	3	3	58.7	1	1	27.7
3	3	89.1	3	3	89.1	3	3	46.5	1	1	24.5
3	**2**	**54.6**	**3**	**2**	54.6	3	3	48.3	1	1	25
1	1	51.7	1	1	51.7	1	1	31.1	2	2	52.8
3	3	69	3	3	69	1	1	30.4	2	2	37.2
2	2	70.7	2	2	70.7	2	2	38.7	**1**	**3**	42.6
3	3	73.1	3	3	73.1	1	1	30	3	3	47.2
3	3	85.3	3	3	85.3	1	1	31.9	3	3	40.3
1	1	49.3	1	1	49.3	1	1	40.5	**3**	**2**	42.6
1	1	55.8	1	1	55.8	1	1	40.1	2	2	31.8
2	2	54.3	2	2	54.3	1	1	33	3	3	39.6
2	2	62.3	**1**	**2**	62.3	1	1	37.3	1	1	32.7
3	**2**	72.5	**1**	**2**	72.5	1	1	29.3	3	3	61.4
2	**3**	73.3	3	3	73.3	1	1	36.4	2	2	35.8
1	1	31	1	1	31	1	1	34.2	2	2	37.2
3	3	86.8	2	2	73.6	1	1	32.9	3	3	68.1
2	**1**	31.7	1	1	46.5	1	1	37.7	3	3	40.4
3	3	66.4	1	1	54.1	1	1	51	3	3	49.1

possible to create predictive models to classify the oils, with a very high degree of accuracy. The predictions of the models are sometimes different from the decisions of the companies, but some of the errors may be due to poor decisions of the companies. Using PCA it was onfirmed that in both companies it is possible to identify oils which were replaced very early and oils which were replaced at a much more advanced degree of deterioration.

PCA also showed that the variables measured during oil analysis have different importance to assess the quality of the oil and predict the company decision. ANN modeling confirmed this result, since it was possible to train a model with very high accuracy using just 10 of the 21 variables.

Table 11 compares the results obtained for dataset AB. It shows the classification of the oil by the human experts, the classification given by the artificial neural network trained with 12 variables and the percentage of oil degradation calculated using PCA. The samples where the classification of the neural model is different from the human expert are marked in bold. As the table shows, there is a large variability of results. But in general the ANN's classification and the PCA classification are coherent and arguably better than the human experts. As a reference, the average average deterioration for class 1 is 37.86 % for the human experts and 37.03 % for the ANN. For class 2 it was 52.07 % for humans and 52.44 % for the ANN. And for class 3, the average deterioration is 73.05 % for humans and 74.14 % for the ANN. The average deteriorations show that the ANN was successful clustering the most deteriorated oils in class 3 and the less deteriorated oils in class 1, more than the human experts.

Looking in more detail at the situations where the ANN and the human classification differ, it is possible to conclude that there is a high probability that some of the misclassifications are human rather than design or training limitations of the ANN. For example, in Table 11 the first error happens in a sample where PCA determines a level of oil degradation of 54.6. That sample was classified by the company as a 3 and by the neural model as a 2. In fact, the average oil degradation for oils classified as 2 is approximately 52. The third error happens for a sample with oil degradation 31.7 according to PCA, which is below the average degradation for class 1 (approximately 37). That sample was classified as 2 by the experts and 1 by the neural network. Many of the remainder errors are similar to the ones already described, which shows the neural model is very much according to the results obtained with PCA analysis.

8. Main contributions

The present paper proposes different novel contributions to the state of the art, which can be highlighted as follows.
- The results show that it is possible to create good artificial neural models to classify the oils. Moreover, the models can perform possibly with even less errors than human experts.
- Using PCA, the relevance of the variables monitored for oil analysis was determined, thus providing a better insight into the importance of each variable.
- The results also show that a good neural model does not need to use all the variables. In fact, a good model was created with just 12 input variables. This helps the process of determining the right time for oil change.

9. Conclusion

Condition monitoring of engines' oil is very important to prolong the engine life, avoid unnecessary pollution and also accidents due to engine overheating or other failures. The present paper describes experiments to create different artificial neural models that can help classify the state of deterioration of the oils with high accuracy. Because of the different policies followed by different companies, it may be difficult to create one single model that fits all policies. But it was possible to create models that showed good performance for two different companies. Those models may even generalize and learn a balance between the two policies. The results of the neural models were convergent with the results of PCA. PCA determines which companies follow the best policies for oil replacement and which variables are best predictors. The present analysis may be useful to help companies make the best decisions at the best time, or even decide which variables are more important to monitor. Future research includes fine tuning the models with more data and proposing a model to automate the process, as well as testing other classification or future extraction techniques

References

1. Capone S, Zuppa M, Presicce D S, Francioso L, Casino F, Siciliano P. Metal oxide gas sensor array for the detection of diesel fuel in engine oil. Sensors and Actuators B: Chemical 2008; 131(1): 125-133, https://doi.org/10.1016/j.snb.2007.12.029.
2. Cerny B A, Kaiser H F. A study of a measure of sampling adequacy for factor-analytic correlation matrices. Multivariate Behavioral Research 1977; 12(1): 43-47, https://doi.org/10.1207/s15327906mbr1201_3.
3. Du L, Zhe J. As high throughput inductive pulse sensor for online oil debris monitoring. Tribology International 2011; 44(2): 175-179, https://doi.org/10.1016/j.triboint.2010.10.022.
4. El-Hag A H, Saker Y A, Shurrab I Y. Online oil condition monitoring using a partial discharge signal. IEEE Transactions on Power Delivery 2010; 26(2): 1288-1289, https://doi.org/10.1109/TPWRD.2010.2073551.
5. Gajewski J, Valis D. The determination of combustion engine condition and reliability using oil analysis by MLP and RBF neural networks. Tribology International 2017; 115: 557- 572, https://doi.org/10.1016/j.triboint.2017.06.032.
6. Ghobadian B, Rahimi H, Nikbakht A, Najafi G, Yusaf T. Diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an artificial neural network. Renewable energy 2009; 34(4): 976-982, https://doi.org/10.1016/j.renene.2008.08.008.
7. Hongxiang T, Yuntao L, Xiangjun W. Application of neural network to diesel engine SOA. Third International Conference on Measuring Technology and Mechatronics Automation 2011; IEEE, https://doi.org/10.1109/ICMTMA.2011.141.
8. Kumar S, Mukherjee P, Mishra N. Online condition monitoring of engine oil. Industrial lubrication and tribology 2005; 57(6): 260-267, https://doi.org/10.1108/00368790510622362.
9. Li X, Li J, He D, Qu Y. Gear pitting fault diagnosis using raw acoustic emission signal based on deep learning. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2019; 21 (3): 403-410, https://doi.org/10.17531/ein.2019.3.6.
10. Li Y, Wang K. Modified convolutional neural network with global average pooling for intelligent fault diagnosis of industrial gearbox. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2020; 22 (1): 63-72, https://doi.org/10.17531/ein.2020.1.8.

11. Niu X, Yang C, Wang H, Wang Y. Investigation of ann and svm based on limited samples for performance and emissions prediction of a crdi-assisted marine diesel engine. Applied Thermal Engineering 2017; 111: 1353-1364, https://doi.org/10.1016/j.applthermaleng.2016.10.042.

12. Parlak A, Islamoglu Y, Yasar H, Egrisogut A. Application of artificial neural network to predict specific fuel consumption and exhaust temperature for a diesel engine. Applied Thermal Engineering 2006; 26(8-9): 824-828, https://doi.org/10.1016/j.applthermaleng.2005.10.006.

13. Raposo H, Farinha J T, Fonseca I, Galar D. Predicting condition based on oil analysis - a case study. Tribology International 2019; 135: 65-74, https://doi.org/10.1016/j.triboint.2019.01.041.

14. Rodrigues J, Costa I, Farinha J T, Mendes M, Margalho L. Modelling diesel engine oil condition using artificial neural networks. eMaintenance 2019, Stockholm, Sweden.

15. Shaban K, El-Hag A, Matveev A. A cascade of artificial neural networks to predict transformers oil parameters. IEEE Transactions on Dielectrics and Electrical Insulation 2009; 16(2): 516-523, https://doi.org/10.1109/TDEI.2009.4815187.

16. Westerholm R, Li H. A multivariate statistical analysis of fuel-related polycyclic aromatic hydrocarbon emissions from heavy-duty diesel vehicles. Environmental Science & Technology 1994; 28(5): 965-972, https://doi.org/10.1021/es00054a032.

17. Yonghui Y, Weihua W, Xinpin Y, Hanliang X, Chengtao W. An integrated online oil analysis method for condition monitoring. Measurement Science and Technology 2003; 14(11): 1973-1977, https://doi.org/10.1088/0957-0233/14/11/015.

18. Zhu J, He D, Bechhoefer E. Survey of lubrication oil condition monitoring, diagnostics, and prognostics techniques and systems. Journal of Chemical Science and Technology 2013; 2(3): 100-115.

19. Zhu J, Yoon J M, He D, Bechhoefer E. Online particle-contaminated lubrication oil condition monitoring and remaining useful life prediction for wind turbines. Wind Energy 2015; 18(6): 1131-1149, https://doi.org/10.1002/we.1746.

20. Zhu X, Zhong C, Zhe J. A high sensitivity wear debris sensor using ferrite cores for online oil condition monitoring. Measurement Science and Technology 2017; 28(7), https://doi.org/10.1088/1361-6501/aa6adb.

João RODRIGUES
CISE, Univ. Beira Interior, Covilhã, 6201-001, Portugal
and
Industrial Eng. and Management, Univ. Lusófona, Campo Grande 376, 1749-024, Lisboa, Portugal

Inês COSTA
Polytechnic Institute of Coimbra – ISEC, Quinta da Nora, 3030-199 Coimbra, Portugal

J. Torres FARINHA
Polytechnic Institute of Coimbra – ISEC, Quinta da Nora, 3030-199 Coimbra, Portugal
and
CEMMPRE, Coimbra University, DEM, Polo 2, 3030-290 Coimbra, Portugal

Mateus MENDES
Polytechnic Institute of Coimbra – ISEC, Quinta da Nora, 3030-199 Coimbra, Portugal
and
ISR, Coimbra University, DEEC, Polo 2, 3030-290 Coimbra, Portugal

Luís MARGALHO
Polytechnic Institute of Coimbra – ISEC, Quinta da Nora, 3030-199 Coimbra, Portugal

E-mails: j.antunesr@hotmail.com, a21260426@isec.pt, tfarinha@isec.pt, mmendes@isr.uc.pt, lmelo@isec.pt