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MONITORING OF ENGINE OIL DEGRADATION AND POSSIBLITIES OF LIFE PREDICTIONS IN COMBUSTION ENGINE

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Abstract

The article entitled Monitoring of engine oil degradation and possibilities of life prediction in combustion engine deals with chronological monitoring of engine oil on the monitored object - a passenger car with a petrol engine. The research concerns the basic physico-chemical parameters of motor oil, where it discusses the operational factors that contribute to its degradation. The theoretical part of the thesis deals with the analysis of the current state of the problem in the chemical composition of engine oils, analysis of the current state of contact indicators of oil quality in lubrication systems of internal combustion engines and analysis of contactless systems "live" evaluating engine oil quality during vehicle operation. The research part of the work includes the collection of operational data, laboratory analysis of oil samples and statistical processing of the results of tribodiagnostic monitoring. This article discusses the 1st phase of extensive long-term research in the field of tribology and operation of the Mitsubishi Lancer 1.5 Inform motor vehicle.

Keywords: engine oil degradation, life prediction, oil quality sensors, predictive algorithms, regression analysis

List of Symbols
AW additives - anti-wear additives
FTIR – Fourier transform infrared
TAN - Total Acid Number
TBN - total base number
TSA - Time Series Analysis
ZDDP - zinc dialkyldithiophosphates

1. INTRODUCTION

The main goal of the research is to determine the most vulnerable chemical parameters of motor oil in terms of degradation and their mathematical description with subsequent prediction of service life in motor oil. Another important goal is to determine a suitable predictive model and its implementation in practice passenger car Mitsubishi LANCER 1.5 Inform with gasoline engine 4A91 (80 kW).

Fig. 1. passenger car Mitsubishi LANCER 1.5

The vehicle was regularly monitored for almost 3 years - from 01. april 2019 to 30. november 2021. During this period, they covered 32,113 km and 2,027 starts/routes. Each start of the vehicle was consistently recorded in the vehicle's operating log, in which the necessary data were collected. During this interval, three sets of the same Valvoline Syn Power 5W-40 oil fill were tested on the vehicle.

2. DESIGN AND INSTALLATION OF EXTERNAL MEASURING STATION

Part of the research was long-term monitoring of a real vehicle (Fig. 1), which was the subject of daily use by a physical person.

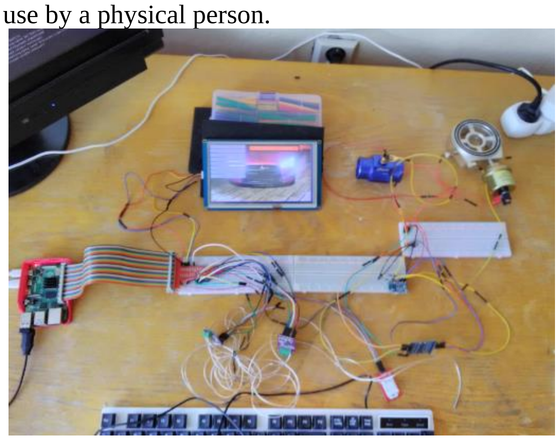

Fig. 2. Raspberry Pi.4 computer test for the Mitsubishi LANCER 1.5 vehicle

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The means of transport was operated in accordance with road traffic rules for the performance of everyday tasks and was regularly serviced. During the monitored period, the vehicle did not perform special tasks (trailer towing, motoring competitions, etc.). This is a vehicle that is not equipped with an oil quality detector, pressure gauge, or thermometer in the lubrication system. It is only equipped with an oil level sensor in the oil tank with a light signal on the driver's dashboard. As the vehicle has only basic equipment, the recording of the vehicle's operational parameters was initially solved with manual portable gauges.

This problem was gradually eliminated by the design of a custom measuring station controlled by a Raspberry Pi.4 single-board computer (Fig. 2., Fig. 4., Fig. 5.) with the possibility of data collection (motor temperature, atmospheric temperature, atmospheric humidity, distance traveled, etc.). The collected and processed data formed the basis for further research operations in R-Studio, WEKA and EXCEL Data Analysis.

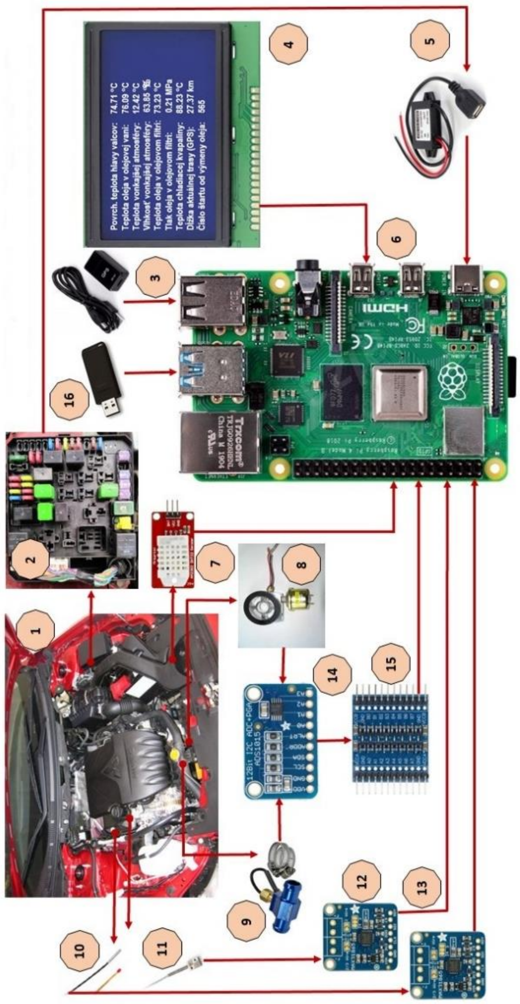

Fig. 3. Principle scheme of the measuring station in passenger car Mitsubishi LANCER 1.5

1. Combustion engine 4A91 Mitsubishi Lancer 1.5 MIVEC
2. Mitsubishi Lancer fuse box
3. GPS locator GF-07
4. Display unit DM12864BV2.0B display
5. Voltage converter CPT 12V-5V
6. Raspberry Pi 4 1.5GHz single-board computer Quad Core 4GB RAM
7. Combined temperature and humidity sensor atmosphere AM2302 DHT22 Digital
8. Reduction for oil filter with temperature sensor oil (QSP) and oil pressure 0400670
9. Reduction of the cooling system with temperature sensor coolant (QSP)
10. Analog oil temperature sensor in the oil pan PT1000
11. analog engine head surface temperature sensor tb02-bb8d-135
12. Adafruit analog/digital signal converter MAX31865 RTD PT100
13. Adafruit analog/digital signal converter MAX31865 RTD PT100
14. Two-way converter of logical signals 5V/3.3V 8 channels for TTL logic
15. 4-channel analog/digital signal converter ADS1015 - ADC I2C - Adafruit 1083
16. USB flash drive

Fig. 4. Installation of a Raspberry Pi.4 computer in a Mitsubishi LANCER vehicle

Fig. 5. Installed display unit of measuring station in passenger car Mitsubishi LANCER 1.5

The picture (Fig. 3) shows an external electronic data collection system on a Mitsubishi Lancer 1.5 Inform vehicle. This external system is not part of the CAN-BUS serial interface, nor a subsystem of another central control unit. The control unit consists of a Raspberry Pi.4.0 single-board computer developed by the British Raspberry Pi Foundation. It operates with the Raspberry Pi OS language built on a modified Linux called Debian. The automated system is powered from the vehicle's electrical network (12 V). The system consists of a number of sensors, signal converters and regulatory elements. The display unit informs the driver "live" about the scanned physical parameters. Scanned data can be backed up to a USB memory stick or SD card. In order to connect the sensors, structural intervention was necessary, especially in the lubrication and cooling system of the vehicle.

3. DATA COLLECTION AND PROCESSING

The main and long-term goal of the research is the mathematical expression of the degradation processes in engine oil and the subsequent approximation of the life of the engine oil. It follows from the above that a large part of the research is focused on the collection and processing of measured data with the design of predictive-approximation mathematical models. This process requires a voluminous statistical base of operating data from the vehicle and from the oil filling. Mathematical models are based on regularly monitored engine oil parameters (Table 1) depending on the nature of vehicle operation in the given Central European climatic conditions, which are sensed by the Raspberry Pi 4.0 measuring station (Fig. 3).

Table 1.: Example of measured value and their allowed statues

Oil parameters
Kinematic viscosity at 40°C [mm²/s]
Kinematic viscosity at 100°C [mm2/s]
AW aditives [%]
Glycol [%]
Nitration [abs/cm]
Oxidation [abs/0,1]
Soot [% wt]
Sulfation [abs/0,1]
TBN [mg KOH/g]
Water content [ppm]

The oil samples were subsequently evaluated in the tribodiagnostics laboratory at the Department of Mechanical Engineering A.O.S. Gen. M.R. Štefánik in L. Mikuláš. The tribodiagnostic analysis was focused on the basic chemical and physical properties of engine oil (Table 1.) using the most modern devices (optical and FTIR analysis) (Fig. 6).

Fig. 6. Devices for optical and FTIR analysis

The discrete Fourier transform is suitable for the analysis of stationary signals, i. e. signals that do not change in time. An oil sample is a typical stationary object of measurement where very precise measurements can be made with the help of FTIR [1].

Mitsubishi Motors Corporation recommends changing the oil after 20,000 km for these types of vehicles, and after 7,000 km in urban and extreme traffic [2].

During the research, the vehicle used Valvoline Syn Power SAE 5W-40 engine oil with ACEA A3/B3/B4 performance specification. The suitability of use is also confirmed by statistics from 2016, where up to 64% of vehicles older than 5 years were guided by this specification when choosing engine oil. In the European Union in 2016 operated approximately 126 million cars older than 5 years [3].

4. PROPOSAL OF APPROXIMATE MODELS FOR CALCULATING THE REMAINING LIFE OF ENGINE OIL

In this case, the proposals of mathematical models relate to the most fragile and monitored long-term parameters of TBN engine oil and AW additives (Tab. 1).

AW additives are lubricant components that chemically react with the metal surface to be protected and form a lubricating coating that protects the metal from wear under extreme lubrication conditions. Anti-wear additives are most often based on ZDDP and ashless phosphoric acid dialkyldithiophosphates, bismuth carboxylates and nano-particle potassium borates. [4]

TBN is a number that characterizes the property of the oil associated with the neutralization of the acidic environment, which is created mainly during combustion and oxidation products. During operation, this ability decreases, i. e. j. the alkaline reserve decreases and the acidity of the TAN increases. The measured value should not fall below 50% of the original value of the new oil. The decrease in this oil parameter is mainly related to the quality of the fuel (sulfur content in the diesel) and the water content in the oil. [5] [6] [7]

The mathematical expression of these parameters makes it possible to create their approximate value and create predictive algorithms for the control unit of the on-board computer, which informs the driver about the current life of the engine oil. It follows from the above that, in addition to displaying data, collecting data and storing data, the designed measuring station can also be programmed with the function of approximating the life of the oil filling. However, the design of the predictor algorithm will be the goal of the next stage of research.

$$\begin{cases} \Sigma y = na + b_1\Sigma x_1 + b_2\Sigma x_2 + .. + b_m\Sigma x_m, \\ \Sigma yx_1 = a\Sigma x_1 + b_1\Sigma x^2_1 + b_2\Sigma x_1x_2 + ... + b_m\Sigma x_m x_1, \\ \text{-} \\ \Sigma yx_m = a\Sigma x_m + b_1\Sigma x_1x_m + b_2\Sigma x_2x_m + b_m\Sigma x^2_m. \end{cases} \tag{1}$$

The essence of the calculation of the current residual life of the engine oil is based on long-term statistical measurements of the vehicle's operating conditions and regular monitoring of the chemical-physical parameters of the oil filling, which was evaluated by laboratory devices (Fig. 6). In the search for the most optimal calculation relationship for determining the life of the oil, mutual relationships were created between the monitored parameters with the search for functional dependencies. The influence of operating factors on the complex chemical-physical picture of engine oil has been monitored and evaluated for a long time. Since the parameters of AW additive and TBN base reserve were the weakest link in the oil, they were determined as the main indicators of engine oil life. On the basis of robust sets (collected operating data of the car and chemical-physical data of the oil filling) when applying correlation analysis and the equation of multiple regression analysis (1), the following calculation relations (2), (3) from 1. and 2. were determined for the mentioned parameters. life stages of the oil filling:

TBN**$_{1stage}$* ***parameter $= 7{,}829165 - 0{,}00723 \cdot S_n + 0{,}000238 \cdot l_n - 0{,}0263 \cdot t_{An} + 0{,}001163 \cdot t_{Mn} - 0{,}001024 \cdot v_{An}$ *[mg KOH/g]* (2)

TBN**$_{2stage}$* ***parameter $= 8{,}465232 - 0{,}00663 \cdot S_n - 0{,}00151 \cdot l_n - 0{,}02876 \cdot t_{An} + 0{,}001409 \cdot t_{Mn} - 0{,}00319 \cdot v_{An}$ *[mg KOH/g]* (3)

***TBN**$_n$* *base reserve at the n^{th} engine start [mg KOH/g]*
***S**$_n$* *n^{th} engine start (serial number of start from the last engine oil changes) [-]*
***l**$_n$* *length of the route with the vehicle at the n^{th} engine start [km]*
***t**$_{An}$* *atmospheric temperature at the n^{th} engine start [°C]*
***t**$_{Mn}$* *engine surface temperature at the n^{th} engine start [°C]*
***v**$_{An}$* *relative air humidity at the n^{th} engine start [%]*

In order for the approximation deviation to be as small as possible in calculations, computational applications use the method of least squares in multiple linear regression, which consists in finding the parameters of the regression function for which the sum of the squares of the deviations of the equalized values of the explanatory variable from the measured values is minimal, i. e. that it is based on minimizing the residual sum of squares. [8]

The mentioned linear equation represents the notation of the n-th line of the statistical dataset. For this case, where the life of the 1st oil filling was related to 800 engine starts, the linear regression equation will be expressed in matrix form as follows:

$$\begin{pmatrix} TBN_1 \\ TBN_2 \\ TBN_3 \\ . \\ . \\ . \\ TBN_n \end{pmatrix} = 7{,}829165 - \begin{pmatrix} 0{,}00723.S_1 \\ 0{,}00723.S_2 \\ 0{,}00723.S_3 \\ . \\ . \\ . \\ 0{,}00723.S_n \end{pmatrix} + \begin{pmatrix} 0{,}000238.l_1 \\ 0{,}000238.l_2 \\ 0{,}000238.l_3 \\ . \\ . \\ . \\ 0{,}000238.l_n \end{pmatrix} - \begin{pmatrix} 0{,}0263.t_{A1} \\ 0{,}0263.t_{A2} \\ 0{,}0263.t_{A3} \\ . \\ . \\ . \\ 0{,}0263.t_{An} \end{pmatrix} + \begin{pmatrix} 0{,}001163.t_{M1} \\ 0{,}001163.t_{M2} \\ 0{,}001163.t_{M3} \\ . \\ . \\ . \\ 0{,}001163.t_{Mn} \end{pmatrix} + \begin{pmatrix} 0{,}001024.v_{A1} \\ 0{,}001024.v_{A2} \\ 0{,}001024.v_{A3} \\ . \\ . \\ . \\ 0{,}001024.v_{An} \end{pmatrix} \tag{4}$$

The principle of approximate calculation of the TBN parameter can be presented in matrix notation (4) for clarity. With the help of this matrix, after inserting the measured, independently transformed operating values of the vehicle, it is possible to calculate the TBN parameter of the engine oil every time the vehicle is started. In the next matrix notation, the actual measured values for the first 3 starts up to the last start no. 800, when the oil exceeded its useful life and it was replaced.

In the previous steps, a multiple linear regression was implemented, the goal of which was to obtain mathematical equations for the exact description of the degradation of the TBN parameter during the two stages of the life of the oil filling (Fig. 8, 9). The third stage of the life of the oil will be the validation stage from the research point of view. Here, the approximate-predictive function of the TBN parameter was determined based on the behavior from the previous 2nd stages and compared with the real results from the 3rd stage. The predictive - approximation function of the TBN parameter (Fig. 10) is created by the intersection of two equations created by regression analysis in the EXCEL Data Analysis environment from the 1st and 2nd stages.

TBN**$_{3stage}$* ***parameter $= 8{,}34858 - 0{,}00693 \cdot S_n - 0{,}00031 \cdot l_n - 0{,}03249 \cdot t_{An} + 0{,}00128 \cdot t_{Mn} - 0{,}00322 \cdot v_{An}$ *[mg KOH/g]* (5)

Equation (5) is the first key mathematical relationship for calculating the actual remaining life of the engine oil. This equation will be implemented in the algorithm of the control unit (Raspberry 4.0

Pi) and the remaining oil life will be displayed on the driver's dashboard display (Fig. 7).

Analogously in the same way as for the TBN parameter, approximation equations for the second most fragile parameter AW additives are determined using multiple regression analysis in the EXCEL Data Analysis environment. For the 1st and 2nd life stages of the oil filling for AW additives (6), (7):

$$\textbf{\textit{AW additives}}_{\textbf{\textit{1stage}}} = 94{,}65432 - 0{,}05057 \cdot S_n + 0{,}009698 \cdot l_n - 0{,}46623 \cdot t_{An} + 0{,}015331 \cdot t_{Mn} - 0{,}003125 \cdot v_{An}\ [\%] \tag{6}$$

$$\textbf{\textit{AWadditives}}_{\textbf{\textit{2stage}}} = 88{,}31146 - 0{,}05322 \cdot S_n - 0{,}005 \cdot l_n - 0{,}37034 \cdot t_{An} + 0{,}026259 \cdot t_{Mn} - 0{,}003232 \cdot v_{An}\ [\%] \tag{7}$$

The third stage of the life of the oil will be the validation stage from the research point of view. Here, the approximate-predictive function of the AW additives parameter was determined based on the behavior from the previous 2nd stages and compared with the real results from the 3rd stage. The predictive - approximation function of the AW additives parameter (Fig. 11) is created by the intersection of two equations created by regression analysis in the EXCEL Data Analysis environment from the 1st and 2nd stages:

$$\textbf{\textit{AWadditives}}_{\textbf{\textit{3stage}}} = 90{,}1084 - 0{,}05179 \cdot S_n + 0{,}00597 \cdot l_n - 0{,}37743 \cdot t_{An} + 0{,}02041 \cdot t_{Mn} - 0{,}00727 \cdot v_{An}\ [\%] \tag{8}$$

Equation (8) is the second key mathematical relationship for calculating the current remaining life of engine oil. This equation will be implemented in the algorithm of the control unit (Raspberry 4.0 Pi) and the remaining oil life will be displayed on the driver's dashboard display (Fig. 7).

It follows from the above that the most fragile parameters of TBN and AW additives determine the service life of the oil filling. The remaining service life of the engine oil is expressed as a percentage value on the driver's dashboard display (Fig. 7).

5. RESULTS AND DISCUSSION

In this case, multiple linear regression proved to be a very suitable and relatively accurate mathematical tool for calculating the degradation of the TBN parameter and AW additives in the oil. At the beginning of the research task, models were built based on TSA, but this method turned out to be inappropriate, because an important component of the time series is the seasonal component. Knowledge of the seasonal course gives us the basis for deciding how to behave in individual periods of the seasonal cycle. It is good to be prepared for high values of the analyzed variable "y" and also for its low values. [9].

Fig. 7. Display unit with approximate calculation of the current remaining engine oil life

The advantages of the regression method in tribological research were applied in a similar way by a team of scientists from the University of Pardubice – the benefit of the proposed and verified methodology presented in the article is a relatively simple way of determining the kinematic viscosity (i.e., ‘physical’ quantity) from the infrared spectrum. This spectrum can also be used not only for qualitative and quantitative analysis of chemical composition, but also for the determination of other ‘non-chemical’ quantities; a multivariate model must be available for them, created from a sufficient amount of quality data. The paper presents a methodology for determining kinematic viscosity 100 °C, but the process of creating a model is generally applicable to a number of other quantities (viscosity index, TBN, TAN, flash point, etc.). [10]

The description of the functions of these parameters in the first two stages reached approximately 95% accuracy level. Since the oil degradation process is very complicated and difficult to predict, this result is very good. It points to correctly selected vehicle operating factors (independent variables) that enter the mathematical model. This was confirmed by correlation as well as regression analysis. It is good that it was implemented on the parameters that are the weakest links of the oil.

As for the prediction itself in the third validation stage, an accuracy in the range of 80 to 90% is an expected and satisfactory result. The fact is that the data measured for prediction were based on only two stages. It is assumed that if this research were to be continued (data would be collected from 3 to 4 stages), the accuracy of the prediction could reach values of 90% or more based on this methodology. Based on regression analysis, the number of engine starts and engine temperature were shown to be the main factors of dependence in relation to oil degradation.

To verify the accuracy, the relative measurement error **δx** method was used:

$$\boldsymbol{\delta_x} = [(x_v - x_m)/ x_m] \cdot 100\ [\%] \tag{9}$$

The relative measurement deviation **δx** is determined as the ratio of the absolute value of the absolute measurement deviation and the conventional true value of the measured quantity. It represents a positive numerical value, often expressed as a percentage [11].

x_v calculation result (value of the calculated value according to the equation)

x_m measured value (real measured value)

When balancing the results, it was additionally shown that, with some similarity, General Motors Corporation-GM Oil Life System is also developing predictive systems for its cars, which also has algorithms with systems of linear equations built into the control units of the vehicles. The Daimler-Chrysler Corporation Flexible System (FSS) or the oil quality evaluation system from the Ford Motor Company also show a certain, though small, similarity in the equations.

However, their accuracy remains questionable. These electronic systems indirectly monitor oil life based on engine operating conditions, i.e. j. they do not measure oil quality by contact method. This is due to the fact that it is difficult for contact sensors of the oil condition to monitor the complex chemical picture of the oil in real time (on-line) when the vehicle is running. [12]

Table 2. The result TBN of multiple regression analysis in the EXCEL Data Analysis environment (1st stage)

TBN 1st stage

Regression Statistics	
Multiple R	0,984573
R Square	0,969385
Adjusted R Square	0,969192
Standard Error	0,282043
Observations	800

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	1999,891824	399,978365	5028,12	0
Residual	794	63,1613438	0,07954829		
Total	799	2063,053168			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	7,829165	0,081484	96,081825	0	7,669215	7,989116	7,669215	7,989116
Start number	-0,007320	0,000060	-121,085639	0	-0,007439	-0,007202	-0,007439	-0,007202
Route length	0,000238	0,000563	0,422973	0,672430	-0,000867	0,001344	-0,000867	0,001344
Atmospheric temperature	-0,026299	0,001766	-14,891447	2,06E-44	-0,029765	-0,022832	-0,029765	-0,022832
Engine temperature	0,001163	0,000477	2,440264	0,014894	0,000227	0,002098	0,000227	0,002098
Atmospheric humidity	0,001024	0,000979	1,045067	0,29631	-0,000899	0,002946	-0,000899	0,002946

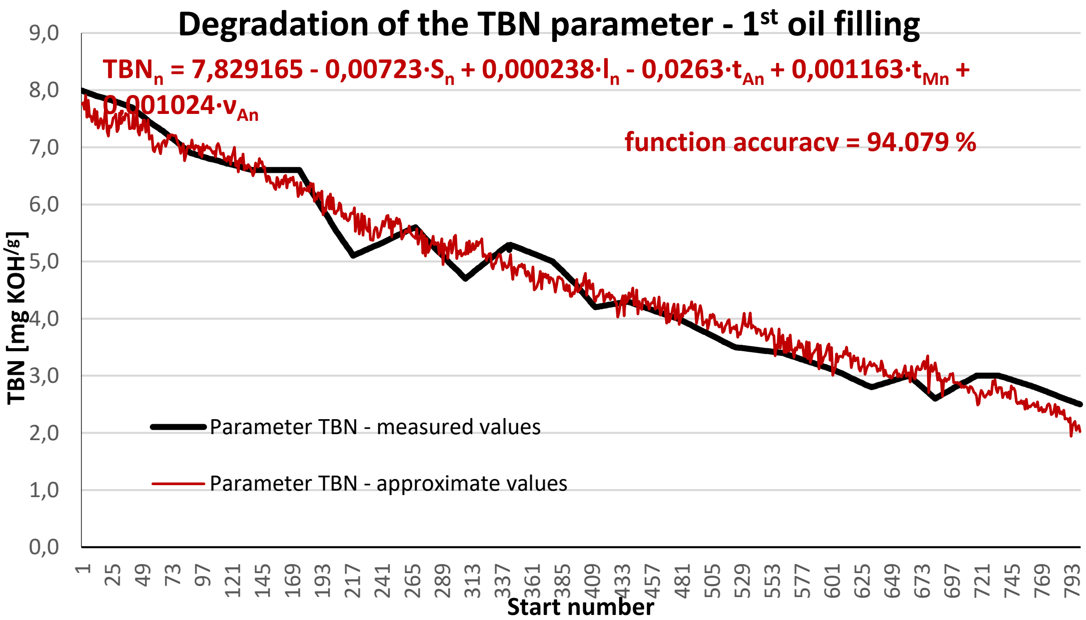

Fig. 8. Approximate expression of the TBN parameter (1st stage)

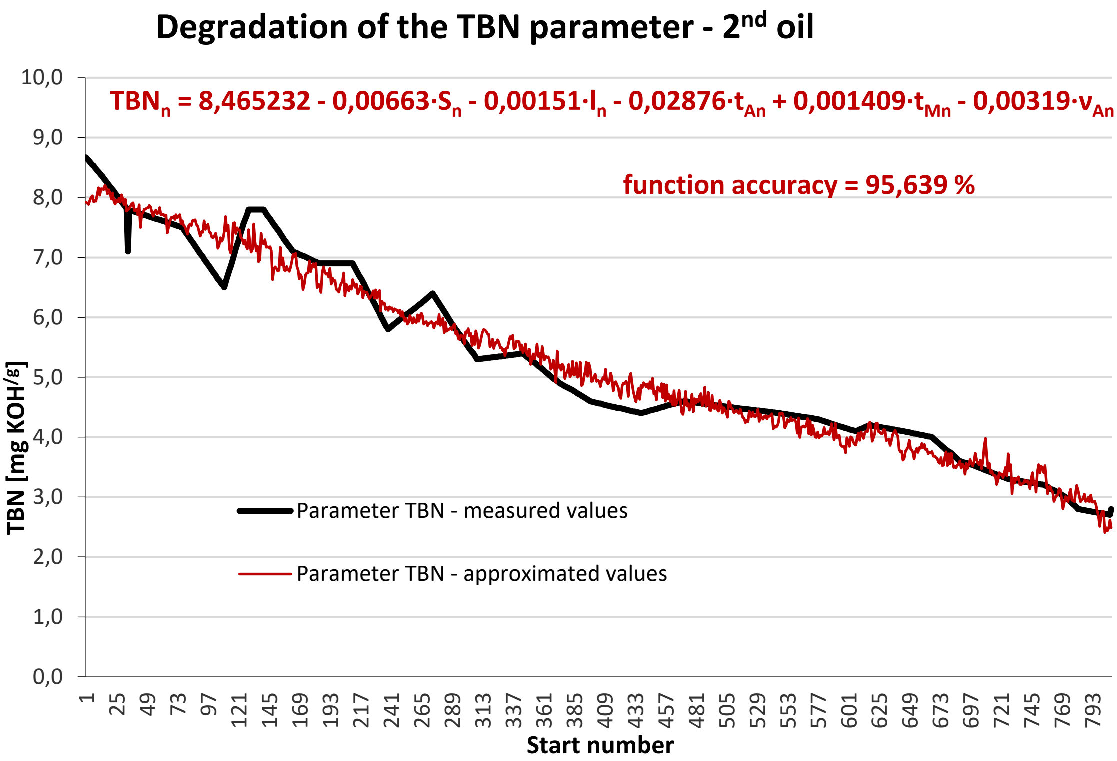

Fig. 9. Approximate expression of the TBN parameter (2nd stage)

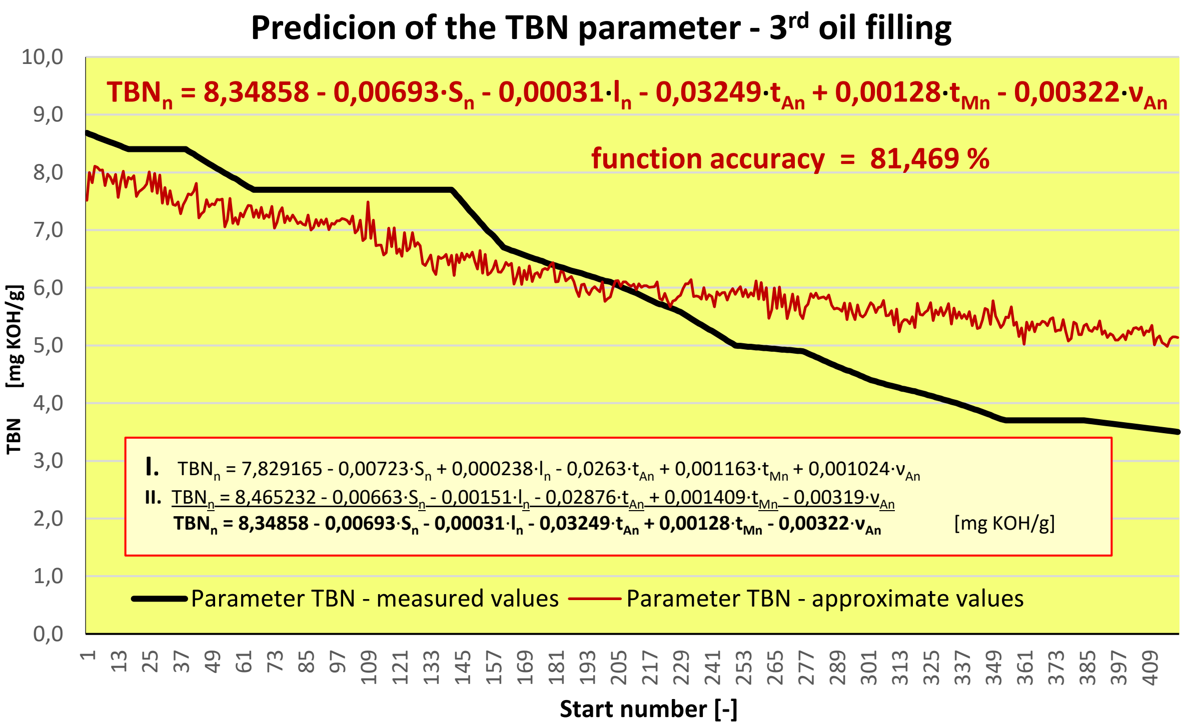

Fig. 10. Verification of the accuracy of TBN parameter prediction (3rd stage)

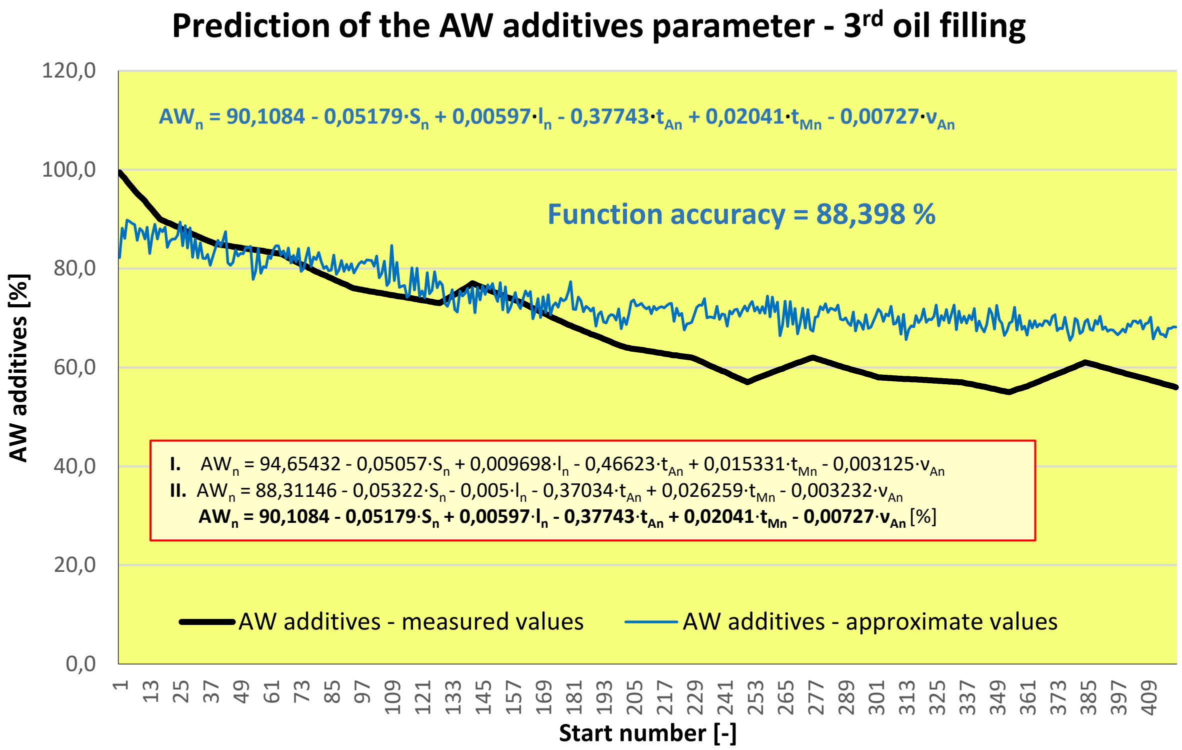

Fig. 11. Verification of the accuracy of the AW additives parameter prediction (3rd stage)

Own calculation model:

***TBN$_n$* parameter** = *8,34858 - 0,00693·S_n - 0,00031·l_n – 0,03249·t_{An} + 0,00128·t_{Mn} - 0,00322·v_{An} [mg KOH/g]* (10)

***AW$_n$* parameter** = *90,1084 - 0,05179·S_n + 0,00597·l_n – 0,37743·t_{An} + 0,02041·t_{Mn} - 0,00727·v_{An} [%]* (11)

TBN$_n$ - *base reserve at the nth engine start [mg KOH/g]*
Aw$_n$ - *AW additive at the nth engine start [%]*
S$_n$ - *nth engine start (serial number of start from the last engine oil changes) [-]*
l$_n$ - *length of the route with the vehicle at the nth engine start [km]*
t$_{An}$ - *atmospheric temperature at the nth engine start [°C]*
t$_{Mn}$ - *engine surface temperature at the nth engine start [°C]*
v$_{An}$ - *relative air humidity at the nth engine start [%]*

General Motors Corp. (GM Oil Life System):

$$T_o = T_{ic} + k_1 \cdot R_e$$
$$T_o = k_2 + k_3 \cdot S_e + k_4 \cdot T_c + k_5 \cdot F_q + k_6 \cdot T_a + k_7 \cdot V_s$$
$$C = k_8 + k_9 \cdot I_t + k_{10} \cdot F_q + k_{11} \cdot T_o + k_{12} \cdot Se \quad (12)$$

T$_0$ - *engine oil temperature[°C]*
T$_{ic}$* , *k$_2$* , *k$_8$ - *locating constants [-]*
k$_1$ *to* ***k$_{12}$*** - *regression coefficients of input parameters [-]*
R$_e$ - *idling speed of the engine [1/s]*
S$_e$ - *engine speed under load [1/s]*
T$_c$ - *coolant temperature [°C]*
F$_q$ - *amount of fuel injected [l]*
T$_a$ - *intake air temperature [°C]*
V$_s$ - *vehicle speed [m/s]*
C - *engine oil degradation rate [-]*

When comparing our mathematical model (10), (11) with a similar system General Motors Corporation GM Oil Life System (12), it can be concluded that our system is focused primarily on the number of engine starts and the climatic environment of the vehicle being operated. The GM Oil Life System is a significantly more complex engine oil life calculation system, where data collection is mainly focused on the engine and its accessories during operation.

Most predictive models are built on kilometer intervals, ie sampling and analysis of the sample is carried out exactly after the observed kilometer interval (1.000 km, 2.000 km, etc.), regardless of the time duration of the interval. The difference between our system and the others lies, among other things, in the fact that the sensing of parameters is exclusively before engine start (many systems read operating variables continuously during engine load), as cold vehicle starts have the greatest impact on oil degradation [13].

It cannot be unequivocally stated that oil quality detection systems have successfully proven themselves in practice. Usually, if the systems are accurate, they only sense a small range of engine oil properties. On the contrary, complex and complex computer-controlled systems offer rather indicative results with relatively large tolerances in terms of accuracy. This is also why these systems are absent in many modern vehicles, and car manufacturers are still reluctant to introduce them into technology. At the same time, the effort to develop them in practice has been going on for several decades. It follows from the above that it is a complex issue, which is a great challenge for the search for new solutions, development and optimization.

The future in this direction probably belongs to spectrum analysers. An advanced contact sensing system was introduced in 2016 by a team of Iranian scientists from Ashtar University of Technology. This system presents a highly sensitive and fast sensing method for "online" analysis of engine oil quality that predicts the remaining life of the oil. The system is based on an optical principle using infrared spectroscopy. The multimode optical film tapers with high accuracy in measuring the refractive indices of fresh and worn oil in mechanical systems. In this system, the length and diameter of the constricted fiber region are optimized by chemical etching at different time periods using 20% hydrofluoric acid. The oil acts as an external medium for this sensor and any changes in the quality, particle size and contamination of the oil consequently affect the optical properties, such as a change in optical power output. By comparing the optical signals between fresh and used oil, accurate oil quality is predicted [14].

6. CONCLUSION

As part of the research task, a new electronic data collection system was designed and installed in the test vehicle Mitsubishi Lancer 1.5 Inform. This system offers a quantity of operational data from the vehicle and wide possibilities for further research.

The testing and finding of the most suitable calculation methods for the mathematical description of degradation processes in engine oil, including the design of mathematical predictive models for the parameters of TBN and AW additives based on modern software (R-Studio, WEKA, Excel Data Analysis) took place.

This research offers a number of results from several years of monitoring oil fillings of the Mitsubishi Lancer 1.5 Inform motor vehicle, which was operated daily. Oil fill monitoring provides a large source of data and information about the vehicle's technical condition. It also defines the course of mutual processes between vehicle operation and oil degradation in the engine type/oil type relationship. Thanks to the collected data from long-term measurements, suitable statistical methods were found to construct mathematical models for the description of degradation processes as well as for their prediction. The result of this part of the work is a universal method for predicting the remaining life of engine oil for gasoline combustion engines of passenger cars. This is another possible solution of a computational approximator that can be implemented for an on-board computer of a motor vehicle.

It can be concluded that the issue of predicting the service life of motor oils is still relevant and is an insufficiently researched area. The absence of related literature and research is also mentioned by experts from the Korean-Swiss team in the article *A predictive algorithm for estimating the quality of vehicle engine oil*, where it is stated that: "There is a lack of more extensive research that would deal with the issue of predictive maintenance in connection with quality of engine oil. Although many works have dealt with engine oil analysis, only a few works have dealt with service life prediction. Therefore, there is no exact guideline on how to estimate the quality of engine oil in view of the nature of its use" [15].

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REFERENCES

1. Kreidl M, Šmíd R. Technical diagnostics – sensors of non-electric quantities. BEN – technical literature 2006; 2: 54.
2. Mitsubishi Motors Europe B.V. MITSUBISHI Lancer, Instruction manual. 2008.
3. Chytka P, Hrabec L, Hrabcová M. Dieselgate – what will happen next? Automotive lubricants from the point of view of ACEA and API standards setters. Professional magazine Tribotechnika 2017; 4: 66.
4. TRIISO, Lubricant Antiwear (AW) Additives, 2020 https://www.tri-iso.com/lubricants-antiwear additives.html.
5. Stopka J. Technical information no. 4/2011 - Undesirable impurities in engine oil for diesel engines. TRIBEX p.r.o 2011; 1-4.
6. Marko M. Bulletin no. 6 - Properties and tribodiagnosis of lubricants in the operation of motor vehicles. ÚLZ Trenčín 2014; 60-61.
7. Post J. Repair and diagnostics III (Second edition). Informatrium Publishing House 2010; 28.
8. Bednáriková Z. Robust regression analysis, Bachelor thesis. Palacký University in Olomouc 2012; 10-11. https://theses.cz/id/ab0jq6/2082943.
9. Chajdiak J. Statistics in EXCEL 2007. Statis Bratislava, 2007; 107.
10. Sejkorová M, Kučera M, Hurtová I, Voltr O. Application of FTIR-ATR Spectrometry in conjunction with multivariate regression methods for viscosity prediction of worn-out motor oils. APPLIED SCIENCES-BASEL 2021; 11(9). https://doi.org/10.3390/app11093842.
11. Gibová Z. Deviations and uncertainties of measurement, record of measurement results. Technical University in Košice 2022; 1-6. http://people.tuke.sk/zuzana.gibova/files/2.kap.pdf.
12. Bommareddi A. An engine oil algorithm. The Pennsylvania State University 2009.

https://etda.libraries.psu.edu/files/final_submissions/392.
13. Lukášik P, Marko M, Sako T. Statistical data processing in R-Studio and WEKA software for engine oil life prediction. Transport Means - Proceedings of the International Conference 2021; 1194 – 1999. https://transportmeans.ktu.edu/wp-content/uploads/sites/307/2018/02/Transport-Means-2021-Part-III.pdf.
14. Ghahrizjani RT, Sadeghi H, Mazaheri H. A novel method for online monitoring engine oil quality based on tapered optical fiber sensor. IEEE SENSORS JOURNAL 2016; 16(10). https://www.semanticscholar.org/paper/A-Novel-Method-foronLine-monitoring-Engine-OilonGhahrizjanSadeghi/1d8a9e08b7ce5f10836a677938d9cfa9692b2972.
15. Hong BJ, Lo Conte F, Kiritsis D, Xirouchakis P. A predictive algorithm for estimating the quality of vehicle engine oil. International Journal of Industrial Engineering 2008; 15(4): 386 – 396. https://journals.sfu.ca/ijietap/index.php/ijie/article/view/186/77.

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