AI military vehicle diagnostics

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***Abstract – This* paper deals with the possibility of diagnosis and prediction of military vehicle failures using machine learning to increase the reliability of military equipment operation and early detection of impending failure. Early detection of incipient faults is absolutely crucial for timely repair planning and thus elimination of downtime in vehicle operations. First, we propose an appropriate method of data acquisition from vehicles considering the cost and efficiency of exploitation. We then propose a suitable approach to fault diagnosis for engine, transmission and brakes using vibration and acoustic diagnostics. These models identify anomalies in engine sound and vibration in the transmission and brake system. In the future, we plan to use these findings to develop a suitable model for machine learning.**

This study presents an effective solution for real-time acoustic monitoring, which is particularly beneficial for remote control and all-weather monitoring, which is then used for evaluation and scheduling of service operations on individual vehicles. This system is equally applicable to current and older equipment.

Keywords-Data acquisition and storage, vibration method, acoustic method, machine learning model.

I. Introduction

The main motivation for writing this paper is the desire to respond to current trends in vehicle diagnostics and early fault prediction and implement these for military vehicle needs.

Since the beginning of the operation of the technology, the aim has been to create a functional maintenance system. These systems help to plan repairs of individual types of equipment appropriately. Appropriate planning helps to eliminate downtime in the operation of the equipment. In military conditions, this is compounded by the requirement for combat capability. Since each vehicle is affected by a different number of external influences in its operation, a different number of failures occur despite the planning and execution of repairs. Depending on the type of fault and which vehicle part it affects, each fault will require, at best, minor service interventions. In the worst case, the fault means that the vehicle is taken out of service and the subsequent long, complicated and costly repair.

In connection with this comes the requirement for timely monitoring of the condition of individual groups and the ability to warn in time of the potential danger of a malfunction and thus the destruction of some vehicle groups.

Diagnostic systems are being developed in parallel with the technologies used in vehicle manufacturing. Currently, the most widely used method of vehicle diagnostics is the On Board Diagnostics (OBD) socket, which has long been part of the on-board system of production vehicles. This is a very simple and easy method that can be used for domestic purposes (with some limitations, of course). For this purpose it is possible to use many freely available applications, e.g. for smartphones (some of them are chargeable). Another issue is the need to purchase a suitable adapter, e.g. see. Figure 1. However, the information obtained in this way is only basic and insufficient for industrial purposes.

Fig. 1: Example of OBD diagnostics

OBD diagnostics uses the outputs from selected sensors within the vehicle infrastructure to perform its function. For example, temperature sensors, pressure sensors, exhaust gas sensors etc.

The authors believe that this method of diagnostics is functional for the needs of the Army of the Czech Republic (ACR), but it has several limitations. The main limitation concerns the fact that older equipment is still used in the Czech Army. This equipment lacks any bus network and thus OBD socket due to the technology of the time. In this case, therefore, OBD cannot be used at all. Another limitation is seen in the software itself needed to perform the diagnosis. Realistically, there are many programs for OBD vehicle diagnostics, but there is no universal tool. Different software is needed for different brands, which also means a different cable needed to connect to the OBD socket. This method of diagnostics is only possible from the vehicle. In practice, this means that the operator (not including the ACR) is forced to outsource this service. In this case, there is a delay in detecting the fault and an increase in the price of any repair.

Therefore, the motivation is to create a system of data collection, prediction and fault diagnostics, which can be used also for the equipment of older production date operated in the conditions of the Czech Armed Forces, based on the knowledge from ML research.

Recently, say 10 years, many companies have been dealing with this issue, both in production and in operation of the technology. Our goal is to introduce and start using these systems within the equipment of the Army. This paper is divided into three main areas: first, the method of data acquisition and storage will be described, then the design of a suitable model for ML for the engine, transmission and brakes will be performed. Finally, the paper will conclude with a proposal to validate the functionality of the model.

II. METHOD OF COLLECTING AND STORING DATA FOR ANALYSIS

This section discusses the possibilities of data acquisition and briefly describes vibration and acoustic diagnostics.

Basically, three types of devices are used for data acquisition and storage: 1) real-time data acquisition systems, 2) data wrigters, 3) data loggers.

In terms of financial requirements, dataloggers are the most affordable.

They offer greater flexibility and have a wide choice of input types. Data loggers usually collect data that can be transferred directly to a computer.

The same collection option is also selectable for some recorders. In this case, it means a further increase in its price.

Data acquisition systems offer a much wider range of applications and are very beneficial when a high sampling frequency is required. However, data acquisition systems require a connection to or installation on a computer which must be in active mode when collecting data, whereas with data loggers, data can be collected independently of the computer. This makes them ideal for portable applications. This option is very often used in motorsport and this is also why we chose dataloggers.

Technically, **a datalogger** is any device that can be used to store data. However, most manufacturers consider a datalogger to be a stand-alone device that can read various types of electrical signals and store the data in internal memory for later transfer to a computer.

The advantage of the datalogger is that **it operates independently of the computer**, unlike many other data acquisition devices. Dataloggers are available in many designs. Simple low cost single channel fixed function dataloggers as well as high performance programmable devices that operate with hundreds of inputs. Several parameters need to be considered when selecting a datalogger, in particular the number of inputs, size, speed, memory and last but not least whether it provides real-time display capability.

Some dataloggers work only with a specific input, others are programmable for different types of inputs.

According to the above, we have chosen the vibration sensing area for our purposes.

Vibration diagnostics is an important part of predictive machine maintenance. Over time, vibration diagnostics has proven to be the most effective method of checking "machine health". Vibration diagnostic instruments help to predict potential machine failure.

In the case of vibration diagnostics, an impending fault can be detected almost immediately.

Every machine that is in operation generates vibrations. The signals of these vibrations contain a lot of information about the parts being inspected. A vibration analyzer or a simpler vibrometer can be used to measure vibrations. The individual sensors need to be applied to a suitable location (e.g. a bearing house). The instrument measures the vibration signal. Based on a suitable processing of the vibration signal, the user receives information about the magnitude, frequency of vibration and thus about possible machine malfunctions. The most common faults of rotating machines are bearing defects, unbalance, misalignment, mechanical loosening...

Other methods are also available to evaluate the condition of the machine and its faults. In addition to vibration diagnostics, these include “ultrasonic fault detection, thermography“. All these methods have their advantages and disadvantages. However, years of operating experience have shown that vibration diagnostics is the most effective and reliable method for monitoring the actual condition of most rotating machinery.

A vibrometer or analyzer is an electronic device that can be used to process vibration signals. The sensor generates a voltage signal which is transmitted to the vibration meter via a cable. The vibrometer is able to process the voltage signal and display vibration values such as acceleration and velocity. See the section on acceleration and velocity.

For proper evaluation, it is necessary to know the vibration limit values that indicate the deteriorating condition of the machine.

For these limit values we can set values according to our experience with certain machines or we can use the ISO 10816-3 standard.

All mechanical defects that are related to the machine speed, such as unbalance, misalignment or mechanical loosening, are considered low frequency vibration.

The most common frequency range for this measurement is 10 - 1000 Hz. This frequency range is also applied in ISO 10816-3. These standards take into account the size of the machine and its mounting. To monitor mechanical machine faults (related to shaft speed), we use a **broadband velocity** measurement in **mm/sec** in the range 10-1000 Hz. We call this measurement a static value because the result is represented by a single number. Using the DDS software, we can track this value over time and observe its evolution (trend).

The specific part of the machine we want to monitor is the bearing. Bearings generate vibrations of higher frequencies due to their design. There is a huge range of bearing types on the market and therefore it is not possible to define general vibration limits. Moreover, each bearing can be operated on different machines with different speeds and loads.

Bearing vibration is measured in acceleration, most often in "g" units. The frequency range of this measurement can be very different. It is important to determine which frequency range is best for a particular bearing.

The second measurement we will include in our regular measurement will be the **broadband acceleration value** in [**g**]. This is again a statistical value represented by a single number.

The reason for the need to measure these two values is that acceleration is more sensitive to high frequency vibrations and velocity is more sensitive to low frequency vibrations. Therefore, it seems to be the most suitable for determining the overall condition of the machine and the bearing.

To start a predictive maintenance program, we use two types of measurements see Fig. 2 at each measurement point under number 1 in Fig.2. These are velocity in mm/s and acceleration in g.

These data cells lie below the measuring point - item 2. There will be multiple measurement points on each machine. On each bearing house of the machine + one in the axial direction on the machine...

The next item is number 3, which is our machine or set.

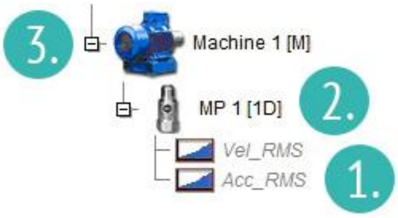

Fig. 2: Example of a measurement chain [8]

After regular measurements, the "**vibration trend**" of the individual values can be compared

Stable trend with acceptable values [Fig. 3]. The machine (or bearing) operates in a stable state and can continue to operate without limitations.

Unstable upward trend [Fig.4]. If the rising value is the result of a **speed measurement, it will be** a mechanical fault related to the machine speed. Unbalance, misalignment or mechanical loosening. If the increasing value is the result of a **measurement in acceleration, it is** most likely a bearing failure.

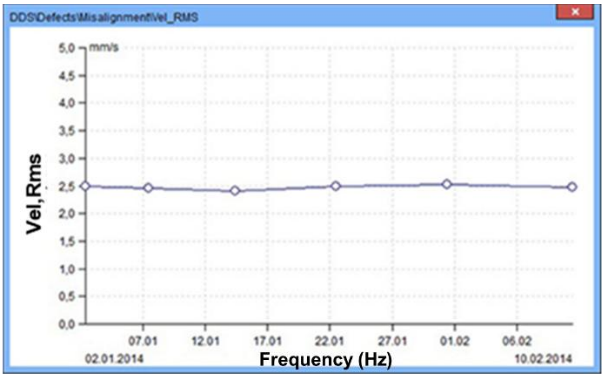

Fig. 3: Stable vibration trend [7]

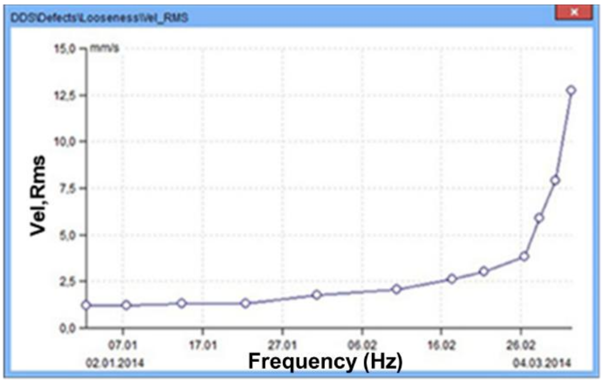

Fig. 4: Unstable vibration trend [7]

It is advisable to store the individual measurement results on a repository where they will be used as part of a data package.

Another method of data acquisition is acoustic diagnostics. Acoustic diagnostics uses the same principles for diagnostic signal processing as vibrodiagnostics. The only difference is the replacement of the vibration sensor with a microphone. The signal here is the sound energy emitted from the measured object. Acoustic diagnostics is a non-contact type of diagnostics and can be performed over longer distances. Its main disadvantage is the influence of the external environment on the measured result. This external environment is very difficult to correct.

III. Designing a Suitable Machine Learning Model

A failure is an unpredictable change in the behaviour of a system that degrades its performance [2].

This chapter discusses suitable failure analysis models for the engine, gearbox and brakes and thus baselines for machine learning purposes

A. The engine:

When operating the engine, users often rely on the detection of rattling sounds that are typical of certain types of damage. In this case, however, the results are very different as it depends on the experience of the user to detect such atypical sounds. Typically, faults such as main shaft bearing knocking, main shaft plain bearing knocking or connecting rod plain bearing knocking, etc. can be detected in this way.

It is therefore desirable to develop an automatic system for the detection and analysis of these faults.

A variant based on the method of identifying marine diesel engine faults based on audio signals presented by Zhou [1] seems to be a possible suitable option. Here, the authors present a system that is capable of classifying various operating conditions in real time. They distinguish between three basic levels: normal operation, abnormal noise, and motor shutdown. At the beginning of the paper, they describe a comprehensive description of the sound data set and the methodology for its acquisition. To obtain the sound data, they placed recording equipment near the cockpit of different vessels. to capture the engine sound well. As part of the measurements, they also captured ambient sounds such as people's voices. Fig. 5 shows a schematic of the measurement chain on a boat engine.

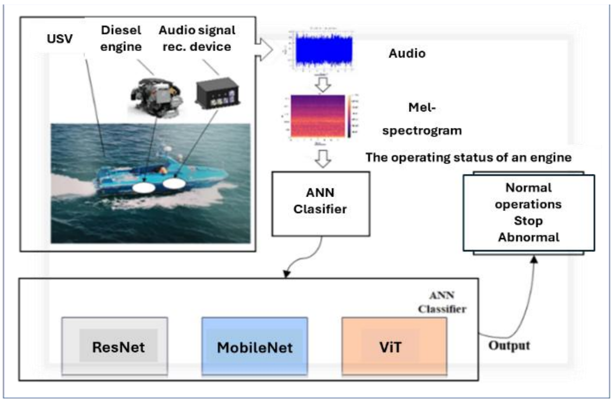

Fig. 5: Block diagram of engine sound signal classification [1]

In doing so, they use various algorithms to generalize and augment the audio signals to increase the model's capability. To extract features from the recorded audio, they then convert these to Mele spectrograms, which allows efficient feature extraction using Convolutional Neural Network (CNN) and Vision Transformer (ViT). They used pre-trained models from the ImageNet-1k dataset to determine the transmission. To assess the accuracy and performance of real-time spectrogram classification, they used three networks: the ResNet50, MobileNet-v3 and ViT-B/16. The ViT-B/16 network was subsequently found to be the best option, with the authors achieving 98.8% accuracy. A graphical comparison of the mentioned networks is shown in Fig. 6, where the x-axis shows the accuracy in % and the y-axis the number of epochs.

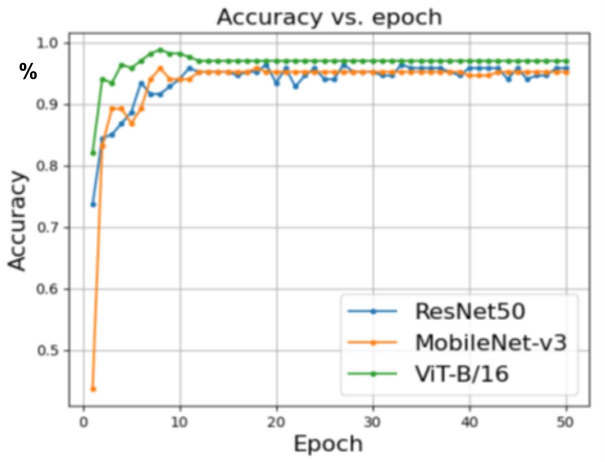

Fig. 6: Comparative analysis of model accuracy [1]

B. Transmission:

Since the gearbox is essentially composed of bearings and gears only, the use of vibrodiagnostics seems to be a better option.

The most common and most likely faults here are damage to the bearings, especially on the outer ring, damage to the bearings damage to the bearings damage to the bearings damage to the bearings damage to the bearings damage to the bearings damage to the bearings damage to the bearings damage to the bearings damage to the bearings damage to the bearings damage to the bearings. For the purpose of obtaining a data set, the results of laboratory measurements can be used. With the help of a test bench and gearbox, input data can be obtained. The test bench is shown in Fig. 7. In this case, it is possible to artificially create certain damages and thus obtain sample data in the case of those damages. The test bench must contain two electric motors. The first motor is connected to the input shaft and simulates the operation of the vehicle engine. The second electric motor shall, on the other hand, be connected to the output shaft and operate in the opposite direction of rotation of the input shaft. In this case, this electric motor acts as a brake and causes a load on the gearbox. Since it is necessary to simulate the correct operating conditions of the gearbox, it is essential that the gearbox is supplied with oil of the correct composition and quality. When testing the gearbox, a gear is selected and an input angular velocity is used in each experiment. Based on the use of a second motor, the gearbox is then loaded. After data is obtained from the gearbox that was faultless, the gearbox with the damage created is measured on the same bench.

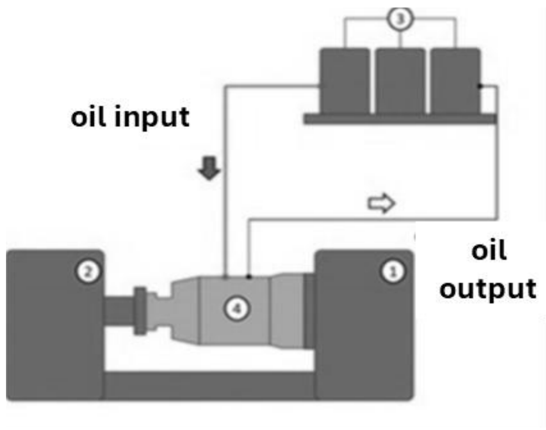

Fig. 7: Schematic of the test station [5]

1 - front electric motor; 2 - rear electric motor; 3 - oil supply and filtration system; 4 - gearbox.

In the case of the measurements in the research conducted in Brazil by Barbieri et al. [5], 5 accelerometers were used for vibration measurements, located in the axes from the upper front bearing, lower front bearing, lower rear bearing, in the x-axis in the intermediate position between the front bearings and in the y-axis in the lower rear bearing. After measuring all the necessary values, bispectrum and scatter were used to verify the visual changes in the signals. Subsequent comparisons were made to determine the difference in signals for each type of damage. Graphs of the comparison of the measured values are shown in Fig. 8 and Fig. 9.

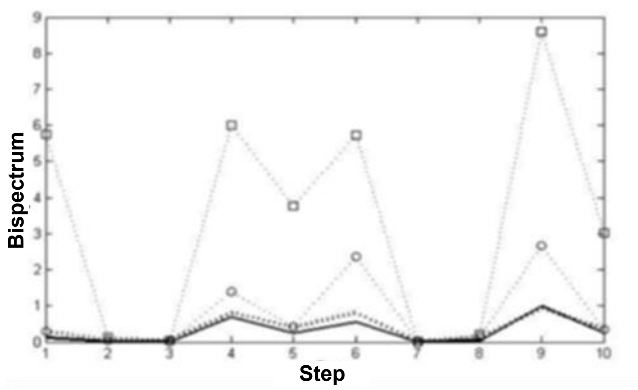

Fig. 8 - Bispectrum curves of the system without and with damage. [5]

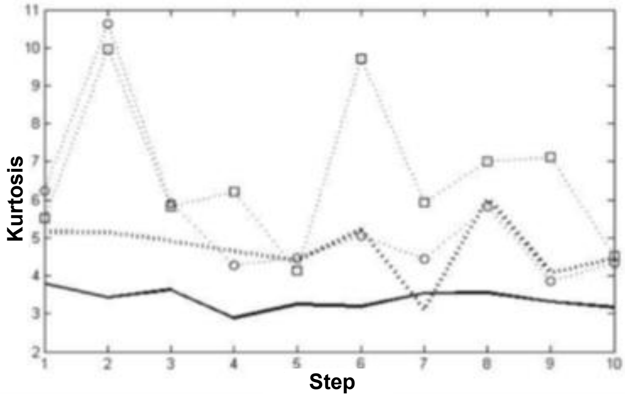

Fig. 9 - Scattering curves of the system without and with damage [5]

Solid line – gearbox without damage, ○ system with damaged rear bearing, □ system with damaged gear.

C. Brakes:

Brake system diagnostics is one of the most important in terms of safety. In the case of the previously mentioned devices, a malfunction means only stopping the vehicle, but a brake failure can mean a risk to human health or, in a worse case, to the user's life. It is therefore very important to pay attention to brake diagnostics. As the brake is a relatively simple device, there is a wide range of possible types of faults, from leaks in the fluid reservoir or brake lines and thus loss of effect due to fluid leaks, to brake lining wear and more. In the past, when designing a suitable diagnostic model, research teams have usually focused on a single fault or group of faults. [4]. Therefore, it is necessary to look at the brake system as a whole and focus on a holistic approach.

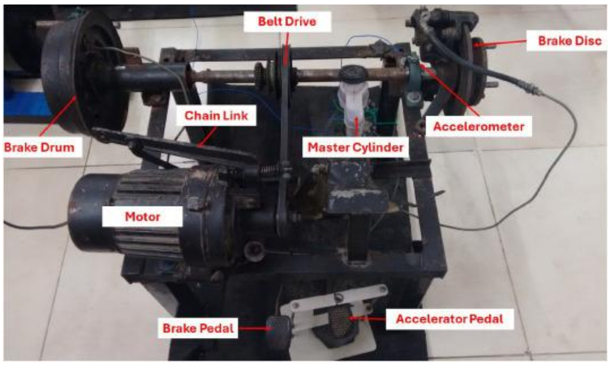

Fig. 10 - Example of an experimental setup for brake diagnostics [4]

The experimental setup for brake fault diagnosis proposed by Viswanathan et al [4] can be seen in Fig.10. A piezoelectric accelerometer was used to capture the vibration signals. The accelerometer was placed near the brake drum (as well as the brake disc). It was then connected by cable to a data acquisition system (DAQ), model NI USB 4432. This DAQ model offers five analogue input channels with a resolution of 24 bits and a sampling rate of 102.4 kilo samples per second. Through the signal conditioning unit, the signal first passes through a charge amplifier and then through an analog-to-digital converter (ADC). Once converted to digital form, the vibration signal is sent to a computer via a USB port and stored in its secondary memory. From there, the signal is read and processed to obtain various functions. Both ends of the cable are used for specific purposes, with one end connecting to the accelerometer and the other to the IO (Input/Output) port of the DAQ system. NI – LabVIEW software was used to interface the sensor signal with the computer system.

Vibration signals were collected from nine fault states and one functional state, resulting in ten separate classes for analysis. These classes included problems such as air in the brake fluid, brake fluid leaks from the disc brakes, changes in disc brake pad wear, drum brake defects, brake fluid reservoir leaks and standard good condition. Initially, the test equipment was considered to be in perfect condition, with all components being brand new. Vibration was recorded from the hydraulic brake system operating at the original speed of 667 rpm and a braking load of 68.67 N (7 kg). A minimum of 55 samples were used for each condition.

From the 50 original samples, the sample with the highest cross-validation accuracy was selected. This selection used the J48 decision tree algorithm.

Once a dataset suitable for symptom classification was completed, the dataset was split 80:20, with 80% retained for training and 20% for testing. In doing so, it was ensured that the segments were equally represented in both the failing and good classes. Eight different classifiers including logistic model trees (LMTs) were then evaluated using a voting algorithm.

The conclusion of this study was that voting is a useful method in diagnosing brake failures. However, the study had some limitations. The performance of the model is highly dependent on the data collected and used for a particular brake system and the failure scenarios generated. This may be different from the actual scenarios. In addition, the study focused on a fixed set of classifiers and feature extraction methods. Future real-time monitoring and adaptive algorithms are a suitable option to explore to simplify on-the-fly fault detection in practical applications.

IV. Conclusions

The article dealt with the possibility of diagnosing military vehicles using machine learning. In addition to methods for collecting data from vehicles for analysis, it also looked at the design of a possible suitable machine learning model for the engine, transmission and brakes. Initially, a choice was made as to the most appropriate method of data acquisition. Subsequently, the predicted fault diagnosis models for engine, transmission and brakes were discussed.

Much of the experience of previous years was used. The fault diagnosis system is already a relatively long-standing process.

The authors' goal is the future implementation of these procedures for the needs of the ACR. If the ACR wants to be a technically advanced institution, it is in its interest to respond to modern trends in the field of fault diagnostics, which in case of its adoption will mean an increase in the reliability of the operation of the equipment and at the same time a reduction in the financial burden needed to carry out repairs of vehicles. As already mentioned, the system envisaged is equally applicable to newly acquired equipment and to equipment of an older date of manufacture, for which the acquisition of spare parts is often problematic. For implementation, it is necessary to create a functional model, then provide a partner for production and, last but not least, tests for use approval within the Czech Armed Forces.

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