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Acquisition of Data for Transmission Diagnostics Using Machine Learning

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Abstract:
This article deals with the design of a system for monitoring gearbox vibrations, which is one of the initial phases of research within a dissertation. This study examines the possibility of diagnosing and predicting failures in military vehicles using machine learning to increase the operational reliability of military equipment and enable the early detection of impending failures. For the purposes of machine learning, it is necessary to obtain a large amount of input data so that it can subsequently be compared with a state in which a potential defect can be observed. Essentially, there are two options for obtaining the input dataset: using a ready-made dataset or acquiring data from a perfect state. A report on this method of data acquisition is the subject of this article. This article presents a real-time vibration monitoring solution that is beneficial for the aforementioned purposes. During the development of this report, efforts were made to utilize commercially available devices to create a cost-effective solution that could be used to acquire input data and subsequently compare it.

KEY WORDS: *Fault prediction and diagnostics system, Acceleration Sensor, Vibration Sensor, Relay Board, Raspberry.*

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1. Introduction

Since the beginning of equipment operation, companies have sought to create a suitable maintenance system. These systems serve to properly plan preventive maintenance or repairs for individual pieces of equipment. Proper planning ensures the elimination of downtime in equipment operation. In military conditions, the requirement for combat readiness is added to this. Many external factors affect each vehicle during operation; therefore, despite efforts at proper planning, a varying number of malfunctions occur. The consequences of malfunctions are diverse. Depending on the severity and which vehicle group is affected, a reduction in the vehicle's functionality may be observed, and in extreme cases, the vehicle may stop and become inoperable, which—especially in combat conditions—can have fatal consequences; returning the vehicle to service often requires a long, complex, and costly repair. In the event of timely detection of an impending fault, often only a minor service intervention is required, or it is possible to better plan the vehicle's downtime for when it is most convenient for the company.

In light of the above, significant effort is devoted to the ability to monitor the condition of critical components and to predict the occurrence of a failure in a timely manner, thereby preventing the destruction of the vehicle's critical systems. There are now many diagnostic tools available. Vehicles can alert to a fault on their own, or external diagnostic devices can be used. In this case, however, the fault has already occurred and often manifests immediately as a functional limitation or a vehicle shutdown, severely limiting the aforementioned planning.

Diagnostic systems replicate the technologies used in vehicle manufacturing; however, it is often necessary to operate equipment that is older and does not support the use of current technologies. Given the enormous diversity of the vehicle fleet, acquiring the necessary equipment and software for diagnostics is very costly, as these diagnostic tools are not fully compatible across the entire spectrum of the fleet.

The goal is to create a fault prediction and diagnostics system that can also be used for older equipment operated under Czech Armed Forces conditions and that fully reflects current trends. Therefore, over time, we would like to incorporate Machine Learning (ML) and AI.

2. A Brief History

Machine learning (ML) is currently a fundamental element in industry, enabling companies to use data to increase efficiency, automate processes, and predict failures. However, the concept of machine learning is not new. A brief overview of the origins of ML:

- The first documented mention of ML dates back to the 1950s, when Alan Turing laid the groundwork by asking whether machines can think (Turing's test).
- In 1959, Arthur Samuel created a program to play checkers. The program learned from its own games and was the first to use the term "Machine Learning."
- 1960s–1980s (Algorithmic Development): Development of basic algorithms, such as the nearest-neighbor method, k-nearest neighbors (k-NN), and the first neural networks (perceptrons).
- 1990s (Shift to Data): Transition from attempting to program rules to training algorithms on large amounts of data. Machine learning begins to be used for data analysis.
- 21st Century (The Era of Big Data and Deep Learning): Increases in computing power (GPUs) and the availability of massive amounts of data (Big Data) enabled the development of deep learning.
- Present (Generative AI): Models such as GPT, launched in 2022, demonstrate advanced capabilities in language understanding and content generation.

3. Selection of Experimental Method

Machine learning analyzes vast amounts of data to identify patterns and correlations. It then stores these insights in models that improve over time and are capable of making predictions or decisions. This means that the system becomes more accurate over time without the need for explicit programming for each specific situation. It is therefore necessary to obtain a basic dataset so that the entire process can begin to function and machine learning can start making comparisons. If the acquired data were not compared with data in a defect-free state, the system would produce incorrect values. Currently, freely available datasets can be obtained, though they do not always correspond to the exact specifications of the parts used in the system; however, they may be very similar. The aim of the experiment was therefore to create a setup that, based on measurements, would help us obtain the required dataset. Several main groups are used in vehicle construction on which various types of measurements can be performed. For the engine, measuring sound pressure density appears to be the most suitable method, as previously performed by Zhou et al. [1]. For the brakes and transmission, the measurement of vibration frequencies by Alamelu [3], Visvanathan [4], and Barbieri [5] is recommended. We chose the measurement of vibration frequencies on the transmission for our experiment.

4. Experiment Overview

The most common and likely failure is damage to the bearings, particularly on the outer ring, and damage to the gears themselves. To obtain a dataset, we first need to create a test setup that will drive the transmission itself, on which the measurements will be performed. In this case, we will use the setup employed in Brazil [5], shown in Fig. 1.

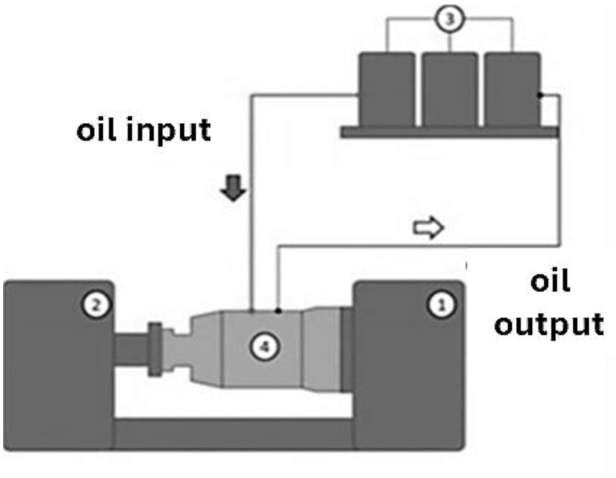

Fig. 1: Schematic of the test station. Adapted from [5]

1 – front electric motor; 2 – rear electric motor; 3 – oil supply and filtration system; 4 – transmission.

The front electric motor is connected to the input shaft and simulates the drive from the vehicle's engine. In this case, the rear electric motor serves as a brake, applying the required load to the transmission and maintaining the necessary rotational speed. It must be connected to the output shaft and must rotate in the opposite direction to the input shaft. For the experiment, it is important that the transmission operates under the correct operating conditions; it is necessary to supply the transmission with oil of the correct composition and quality.

For the vibrometer or accelerometer, we have established the following parameters within the required frequency range:

- IEPE/ICP compatibility (required by MCC 172)
- Frequency range of at least 10 kHz
- Sensitivity of 10–100 mV/g depending on the expected amplitude
- Low noise for detecting subtle defects (pitting, gear mesh)
- The PCB specifies that the sensor must cover 3.25× the gear mesh frequency of the transmission

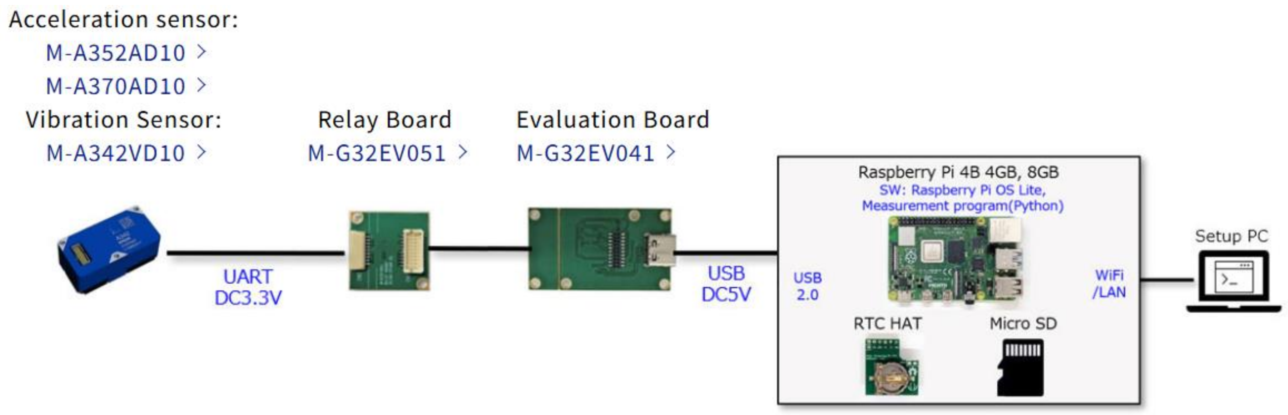

Fig. 2: Intended measurement setup. Adapted from [12,13,14,15]

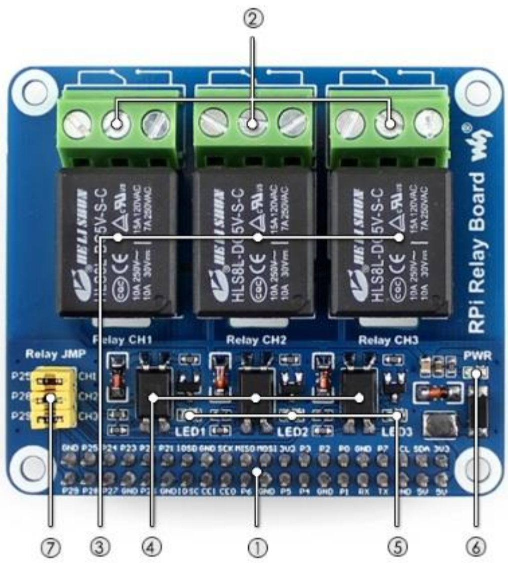

Fig. 3: RPI Relay Board. Adapted from [11]

The Relay **Board** is used to control high-voltage or high-current devices (e.g., 230V appliances) using low-voltage signals from microcontrollers (Arduino, Raspberry Pi). It functions as an electrically controlled switch that galvanically isolates the control section from the power section, thereby protecting sensitive electronics from damage. 1) Raspberry Pi GPIO interface: for connecting the Raspberry Pi, (2) Relay screw terminal: for connecting target devices, (3) Relay, (4) Photocell: PC817, (5) Relay indicator, (6) Power indicator, (7) Relay control switch.

The **M-G32EV041** Evaluation Board (also referred to as a USB evaluation cable interface board) is used to **connect, configure, and test inertial measurement units (IMUs) and accelerometers from a PC via a USB interface**. This board acts as an interface that converts the sensor’s communication protocol to the USB standard for easy data analysis on a PC.

The **Raspberry Pi 4B** is a powerful, affordable single-board computer the size of a credit card, used for teaching programming, home automation, multimedia centers, or as a lightweight desktop PC.

Key features of the Raspberry Pi 4B:

- **Performance:** The Broadcom BCM2711 quad-core processor (1.5 GHz) provides sufficient performance for common tasks.
- **Memory (RAM):** 1 GB, 2 GB, 4 GB, or 8 GB LPDDR4 variants.
- **Connectivity:** Gigabit Ethernet, 2x USB 3.0, 2x USB 2.0, 2x microHDMI (4K support).
- **Power:** USB-C port.
- **Operating system:** Most commonly Raspberry Pi OS (formerly Raspbian), based on Linux.

The assembly ensures compatibility, and we are currently working on placement options and mounting methods for the monitored object.

The number of accelerometers used will be determined later. The placement of individual accelerometers may, for example, be intended on the axes of the upper front bearing, lower front bearing, lower rear bearing, on the x-axis in an intermediate position between the front bearings, and on the y-axis in the lower rear bearing, or in the areas of individual gears.

When testing the transmission, one gear ratio is selected for each experiment, and an input angular velocity is applied. The transmission is then loaded using a second motor. After obtaining data from a fault-free transmission, the transmission with induced damage is measured on the same test bench. To obtain a larger amount of input data, we will also utilize commercially available datasets mentioned in the article.

Limitations. Further research will be needed to draw conclusions. Subsequently, an analysis will be required to determine whether this approach would be beneficial for use in military conditions.

It will be necessary to determine the correct placement of individual sensors on the vehicle, where a decision will be made regarding application to a specific vehicle type.

A limiting factor for this method is the wide range of components used, such as bearings, which may exhibit different values; therefore, it will be necessary to expand the input data to correspond to the components used in the specific vehicle model.

5. Conclusions

This article describes the initial phase of research into real-time diagnostics of military vehicles using machine learning, artificial intelligence, and cloud data storage. A data collection method and test subject were identified. A test setup design was created, and we configured the required parameters for individual components. We developed several setup variants across different price categories. We selected the most suitable variant for our research and identified the transmission components on which our research will focus.

The next step will be to collect input data and create a suitable model for machine learning. In the next phase, we will simulate several types of failures on the same object, then repeat the data collection and evaluate the results using the created model.

I see the benefit for the military in the possibility of real-time diagnostics and, in the future, the transfer of data to cloud storage or computing technology, where it will be possible to immediately evaluate an impending failure and plan the necessary maintenance steps. Furthermore, this method can also be used with older technology where current technologies cannot be applied.

Given that the military currently relies on existing technologies, which are mostly capable of diagnosing equipment through vendor-provided systems—particularly newer equipment equipped with an OBD 2 interface—it is anticipated that once the aforementioned system is developed, this method will be applicable in military settings in the future, and not only from a financial standpoint.

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