DOI 10.5162/ettc2022/9.1

VeDAS Vehicle Data Acquisition System

Martin Bussas
Trout GmbH, Parkstraße 28, 34119 Kassel
m.bussas@trout-gmbh.de

Abstract

Predictive maintenance with machine learning is a new challenge for the automotive industry. Depending on the level of vehicle use and the load on components beyond predefined limits, the detection and elimination of systematic faults and the introduction of demand-oriented maintenance helps increase efficiency and reduce costs.

With this in mind, TROUT has developed VeDAS, a self-sufficient system that can be easily adapted to different vehicles. It is used for the automatic acquisition of vehicle data, which is evaluated with machine learning. Fast and secure communication to the downstream evaluation system is ensured via mobile storage media or wireless communication.

Collected data includes position, acceleration and vibration of the vehicle, as well as speed and distance travelled. In order to take possible environmental influences into account, temperature and humidity are also determined. A structure-borne sound microphone provides information about the operating status of the monitored vehicle. Further data provided by an engine control unit can be accessed via CAN bus interface.

In addition to data acquisition, VeDAS also provides a logbook function for documenting maintenance activities. Maintenance intervals and deadlines are determined for all entered vehicle assemblies. The selected method of condition monitoring specifies maintenance intervals and ensures the availability of the vehicle. Expanded functions include determining when an engine oil change is due.

Key words: machine learning, structure-borne sound microphone, vehicle data acquisition, predictive maintenance

Fig.1 VeDAS Box

DOI 10.5162/ettc2022/9.1

Structure of the Evaluation Software

Data from the VeDAS box is transferred via USB connection to the evaluation software, which runs on a laptop computer. Tabs give access to the collected data and the calculation functions.

- Vehicle data: Creation and modification of vehicle master data, summary of all vehicle data.
- Vehicle usage profile: Evaluation of the data after a selectable period according to terrain and environmental data.
- Graphical representation: Route of the vehicle, structure-borne noise, nick and gear rates, acceleration and speed, shock diagram.
- Assemblies: Organization of the condition-monitored components
- Settings: language, directories, export properties, time zone, definition of limit values and correction factors.
- VeDAS data transfer: Configuration of data import from the VeDAS Box.
- VIN: Vehicle-specific identification numbers and identifiers as well as the date for the last maintenance, the next maintenance and the last data import can be found here.

The data is used for further training and for remodeling the intelligent evaluation module using various Machine Learning methods.

The trained network is then made available within a software update to the evaluation PCs.

Shock Diagram

The diagram shows the number of shocks for the respective load range.

The user can choose between two forms of visualization. The bar chart and a cumulative sum chart. The cumulative sum is formed starting from the highest g-values (here > 2g). The lowest value in the graph, here > 0.2 g, thus indicates the total number of shocks. The user determines in the settings from which g-limit value a measured value is assessed as a shock.

If the number of shocks in a certain range (in the example below >2 g) exceeds the limit value, maintenance is required.

The user defines the limit values for this in the settings.

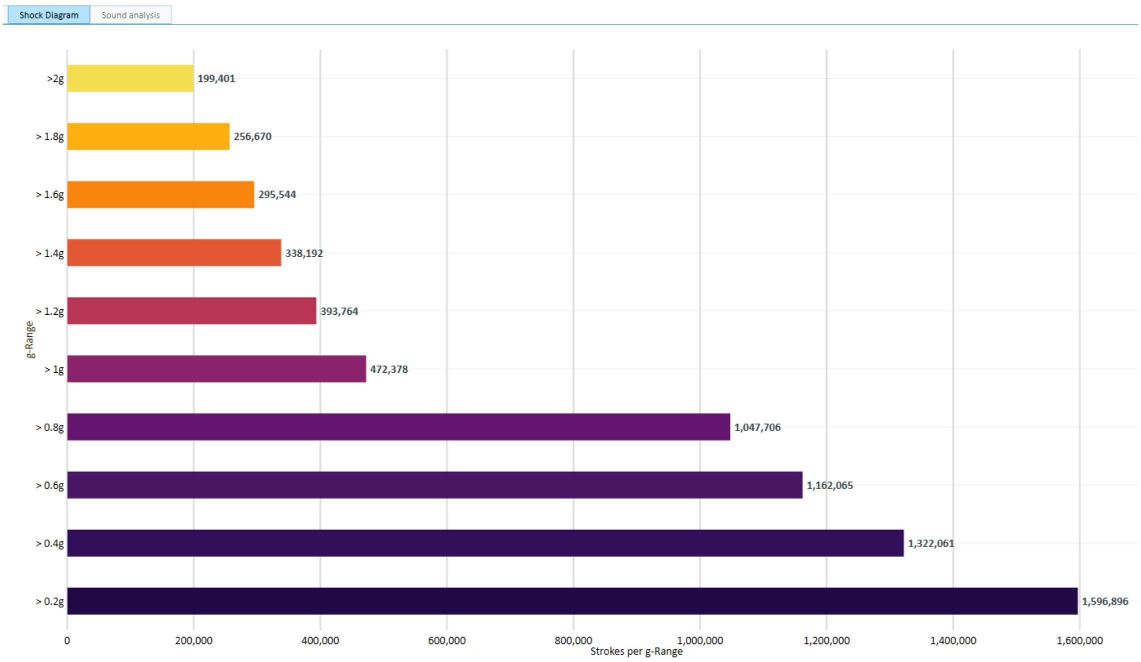

Fig. 2 Shock Diagram, cumulative sum chart

Acceleration and Speed

The shocks in the chapter above are measured via built-in acceleration sensors. In addition, the accelerations for the 3-space axes can be displayed. The speed of the system/vehicle is determined via GNSS. If there is a connection to the vehicle CAN bus, the speed can also be obtained from there. (diagram overleaf)

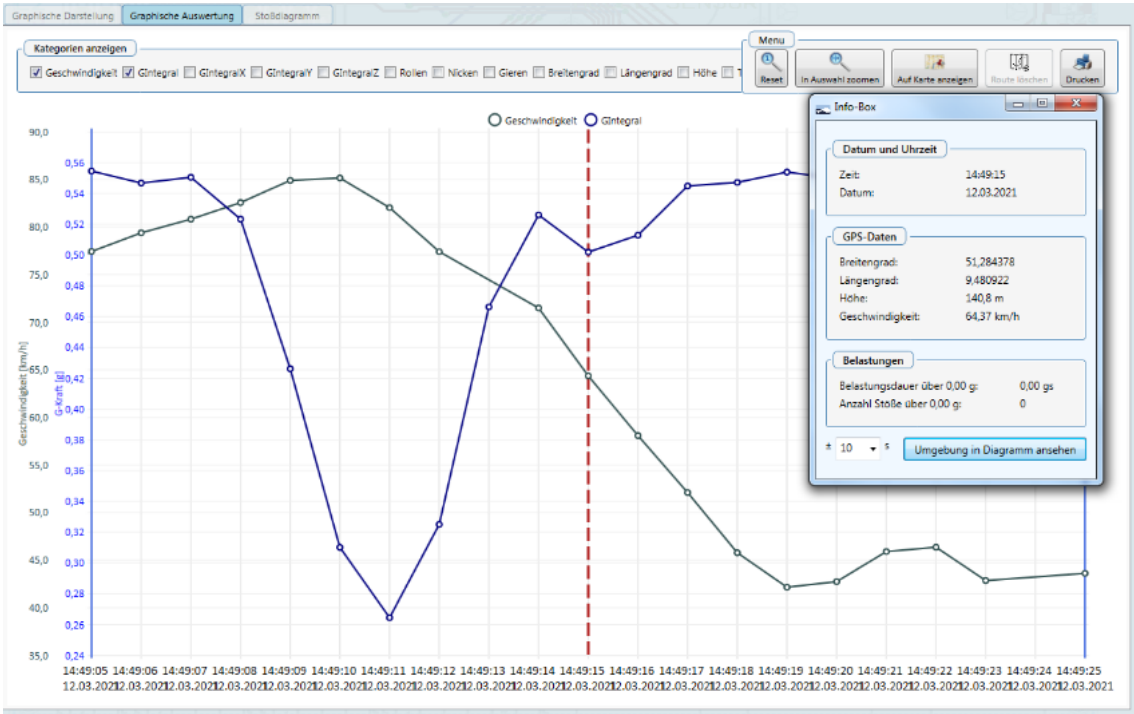

Fig. 3 Acceleration and Speed

Nick and Gear Rates

In addition to the experienced accelerations, the spatial position of the system is recorded. The system shows the deviation from the configured zero position for the parameters roll, pitch and yaw.

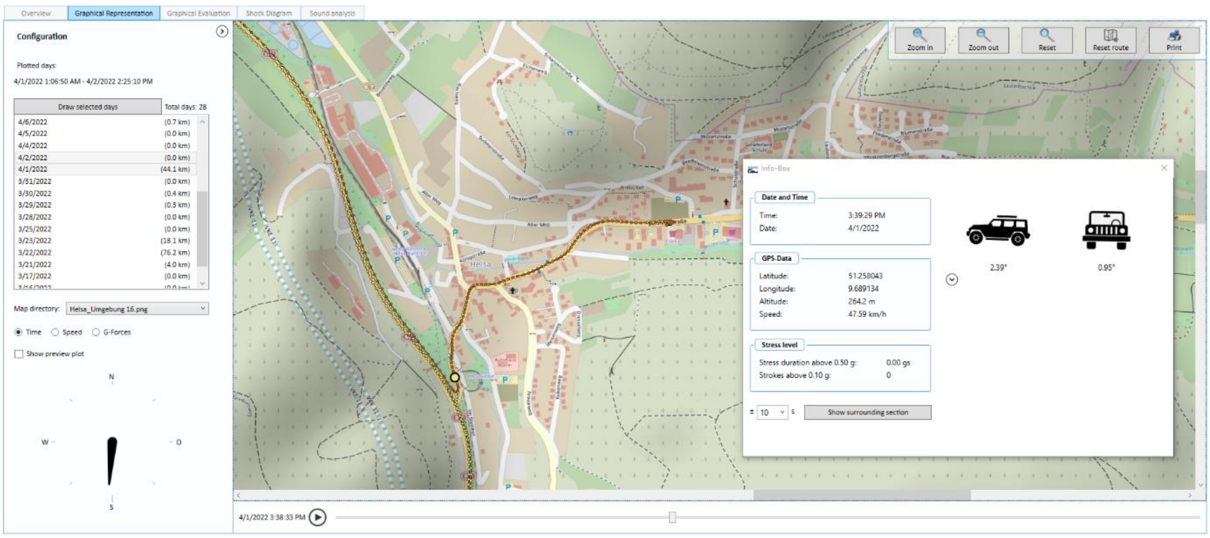

Fig. 4 Nick and Gear Rates

Usage Profile of Vehicle

The evaluation module provides information about the usage profile of the vehicle. The terrain sections are calculated as well as the kilometers driven on the road. The temperature and humidity are also recorded. A velocity profile is presented in tabular and graphical form. (diagram overleaf)

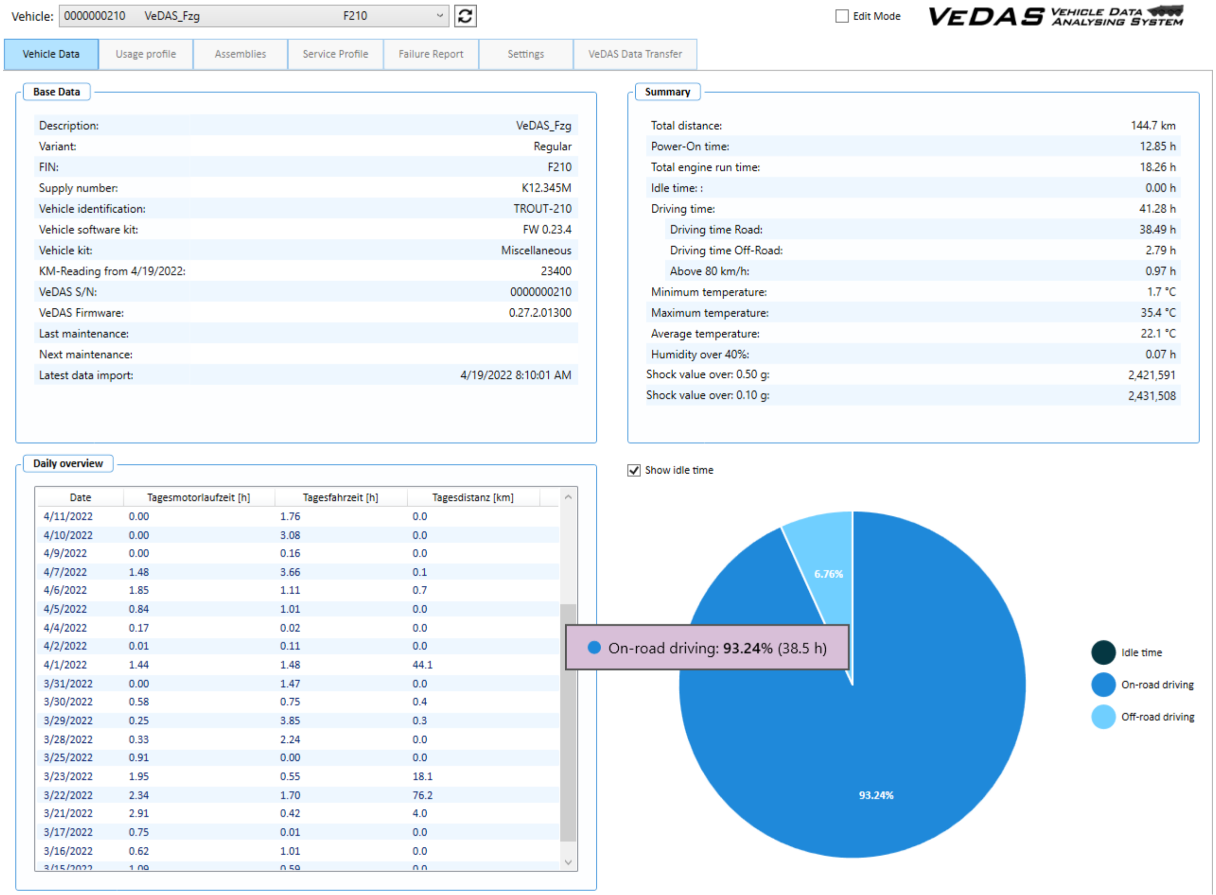

Fig. 5 Usage Profile of Vehicle

Structure-borne Noise

The recorded structure-borne sound [1];[2] can be output directly (green graph). Furthermore, individual frequency components can be displayed (yellow graph). The aim is to assign changes in frequency and amplitude to a defect in the vehicle by means of intelligent evaluation via Machine Learning. [3].

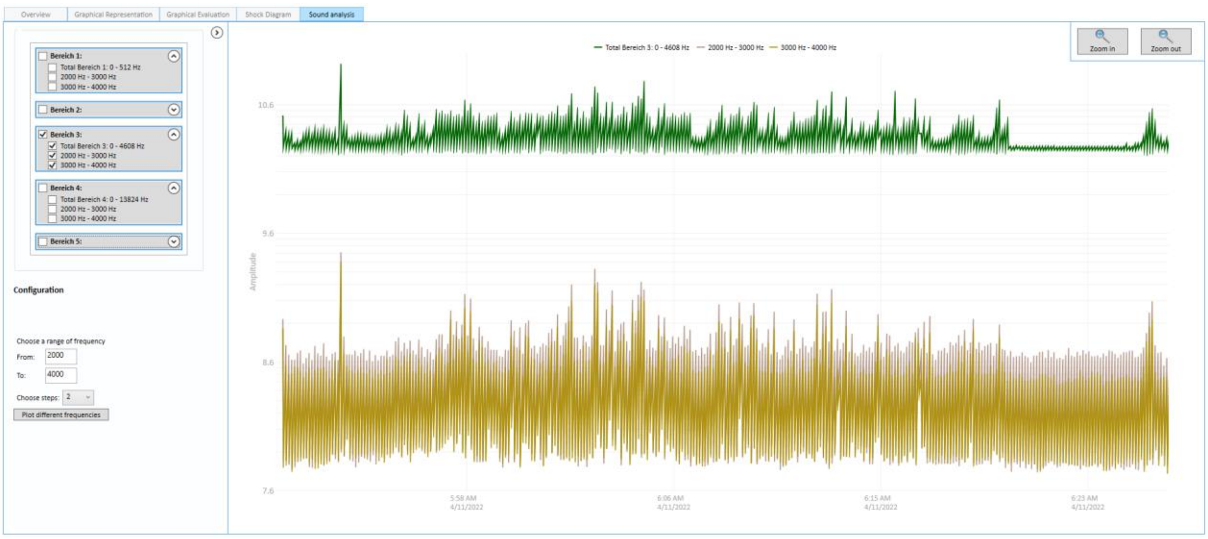

Fig. 6 Structure-born Noise

DOI 10.5162/ettc2022/9.1

Data Process Chain

Vehicle data from the CAN bus and sensors connected to the VeDAS Box are written to a ring memory after filtering with data reduction and a plausibility check. The capacity of the ring memory includes measurement data of several months.

The data can be exported from the ring memory to a database on a PC/laptop at any desired time. There, the data can be evaluated and visualized via a pre-installed artificial intelligence module. In particular, statements are made about maintenance work that is likely to be necessary and the oil quality

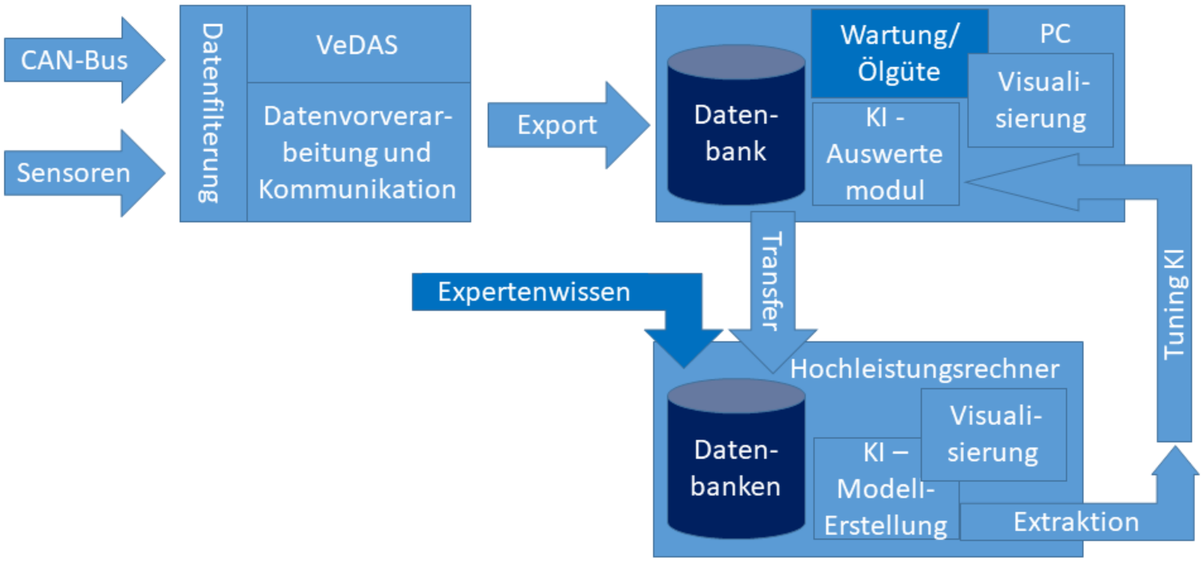

Fig. 7 Process Chain

The data is transferred to a high-performance computer system for further training and for remodeling the intelligent evaluation module using various Machine Learning methods. There, further training of the artificial neural networks takes place with the involvement of expert knowledge. The trained network is then made available within a software update to the evaluation PCs.

In further processing, an additional software component can be used to establish a relationship between the parameters operating hours, engine speed, oil pressure, oil temperature, water temperature, oil pressure profile and a key figure for the oil quality for a specific vehicle type and a specific type of oil. Start is with a default parameterization.

The procedure for calculating potentially required maintenance work on vehicle components is analogous. An evaluation of the measured structure-borne noise spectrum is also included here. The frequency range from 20 Hz to 60 kHz is considered.

Measuring the entire frequency range in one measurement would generate a very large amount of data, since a long period of time would be required to measure low frequencies. It therefore makes sense to carry out several measurements for different frequency ranges, in which the amount of data can still be evaluated.

The initial configuration of the sensor consists of a set of three frequencies and three measuring intervals. (Duration of measurement TM1, TM2, TM3 and measurement frequency MF1, MF2, MF3).

The sensor carries out the configured measurements in a loop:

1. Measuring with TM1, MF1

2. Evaluate data and send to the main processor for storage

Step 1 and 2 are repeated with TM2, MF2 and TM3, MF3. The AI evaluation is then used to search for patterns of sound characteristics of incipient defects in vehicle parts in order to plan an exchange at an early stage if necessary.

Predictive maintenance is the logical continuation of condition monitoring, which has long been integrated into many vehicles as a further development of the classic recording of operating hours. While condition monitoring only enables the detection of a state of wear, with predictive maintenance a maintenance appointment can ideally be scheduled well in advance. As a consequence, this results in higher availability and reduced costs.

Reduce of costs and increase performance

All relevant information is available via the vehicle data from the CAN bus communication plus the data from an additional sensor box in order to recognize whether the vehicle is in the best technical condition or that there are imminent defects. Maintenance can then be planned in advance, vehicle downtimes reduced and breakdowns avoided. This lowers costs, increases performance and extends the service life of the vehicle.

Especially if a special vehicle is used in comparatively small numbers but distributed worldwide, the expense of an additional sensor box with downstream evaluation of the parameters combined with the CAN bus data via machine learning processes pays off. Because, firstly, good predictive maintenance makes some visits by a service technician unnecessary. Second, the vehicle is only serviced when wear and tear requires it. And finally, thirdly: If a technician has to travel, then he knows in advance where the fault lies and, if necessary, which spare parts he needs on site.

Predictive maintenance is particularly attractive in scenarios in which a small malfunction or intervention that is too late can cause extremely high damage.

If the status data is evaluated regularly, the predictive maintenance system sounds an alarm before system failures occur. Then costly consequences can usually be avoided.

Predictive maintenance thrives on the leading system evaluating sensor data and drawing conclusions about the actual wear and tear of the respective component and its remaining service life. The effect of a predictive maintenance model is greater, the more sensors deliver data. And: The more precisely the system works, the more precisely it can be determined when which component should be replaced - in good time before a failure, but also only when it is actually necessary.

To do this, the prediction model must constantly adapt to the circumstances. This means that the measurement data collected must be interpreted continually, and the interpretation should increasingly approximate actual requirements.

This is exactly the function of machine learning algorithms. With their help, functional relationships can be derived from the data, which allow a reliable diagnosis of the status of the monitored system and reliable forecasts. The first goal is therefore to predict the Remaining Useful Life (RUL) of vehicles and components as accurately as possible. The second goal is the already mentioned learning effect. This is because the algorithms not only automate predictive maintenance. They also deliver adequate results and, if necessary, recommendations for action if there are changes in the behavior of the vehicles, but also in the general conditions.

On this basis, maintenance processes, intervals and stocking of spare parts can be optimally adapted to the current conditions. And the model helps to identify deviations before the vehicle is no longer fully functional or major damage occurs. Incidentally, this can also be used for lubricants and consumables. Their condition and wear can also be monitored and the optimal maintenance and replacement times can be derived from this.

For a predictive maintenance project using machine learning, the database must first be examined carefully. It is good if the vehicles to be integrated were already equipped with sensors and these can be read out via log books and log files.

The first step is to view and evaluate the data. What is particularly interesting here is which status or measurement data is collected from vehicles at specific times and since when. Unstructured data such as audio signals/structure-borne noise data can also be viewed and evaluated using additional sensors, such as those available via VeDAS. Not to forget static data such as the Vehicle Identification Number VIN, date of manufacture, supply number, vehicle identification, vehicle software kit and conversion kit.

The next step, the processing, is crucial: the data records have to be cleaned up, wrong values deleted, missing values filled in. At the same time, it is important to develop an understanding of which data was collected, how and under what circumstances.

Conclusion: Companies that pursue ambitious goals with predictive maintenance must integrate artificial intelligence or machine learning. Because only with AI can the value creation potential of predictive maintenance be optimally exploited.

References

[1] Michael Möser, Wolfgang Kropp, Körperschall Physikalische Grundlagen und technische Anwendungen, 2010 ISBN: 978-3-540-49048-7

[2] Michael Möser, Körperschall-Messtechnik, 2018 ISBN: 978-3-662-56621-3

[3] Bernd Orend & Ingo Meyer Schadensfrüherkennung mittels Körperschall, 2009 MTZ - Motortechnische Zeitschrift volume 70, pages 386–391