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Data-driven Condition Monitoring in Mining Vehicles

Erik Jakobsson

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The cover: The background photo shows the Epiroc Minetruck MT65 in an underground mine. ©Epiroc.

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For Katie

Abstract

Situation awareness is a crucial capability of any autonomous system, including mining vehicles such as drill rigs and mine trucks. Typically situation awareness is interpreted as the capability of an autonomous system to interpret its surroundings and the intentions of other agents. The internal system awareness however, is often not receiving the same focus, even though the success of any given mission is completely dependent of the condition of the agents themselves. The internal system awareness in the form of vehicle health is the focus of this thesis.

As the mining industry becomes increasingly automated, and vehicles become increasingly advanced, the need for condition monitoring and prognostics will continue to rise. This thesis explores data-driven methods that estimate the health of mining vehicles to accommodate those needs. We do so by utilizing available sensor signals, common on a large amount of mining vehicles, to make assessments of the current vehicle condition and tasks. The mining industry is characterized by small series of highly specialized vehicles, which affects the possibility to use more traditional prognostic solutions.

The resulting health information can be used both to aid in tasks such as maintenance planning, but also as an important input to decision making for the planning system, i.e. how to run the vehicle for minimum wear and damage, while maintaining other mission objectives.

The contributions include: a) A method to use operational data to estimate damage on the frame of a mine truck. This is done using system identification to find a model describing stresses in the structure with input from other sensors such as accelerometers, load sensors and pressure sensors. The estimated stress-time signal is in turn used to calculate accumulated damage, and is shown to reveal interesting conclusions on driver behavior. b) A method to characterize the different driving tasks by using an accelerometer and a convolutional neural network. We show that the model is capable of classifying the vehicle task correctly in 96 % of the cases. And finally c), a system for underground road monitoring, where a quarter car model and a Kalman filter are used to generate an estimate of the road profile, while positioning the vehicle using inertial measurements and access point signal strength.

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I am also grateful for my children Sofie and Björn, whom without this thesis would probably have taken a year less to complete.

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Erik Jakobsson

Örebro, Sweden
October, 2019

Contents

Chapter 1

Introduction

Who will make sure a vehicle is functional when there is no operator on board? Who will decide what operating point is most cost efficient, considering both the productive output of the machine and the inevitable wear and tear caused by using it? These are important questions arising as more and more vehicles become autonomous.

The global mining industry is currently facing a huge transition from mainly manually operated individual vehicles, to autonomous vehicles being part of an industrial process-like environment. Combined with the never ending demand for more efficient systems, this results in complex vehicles with numerous subsystems and parts. Any of these parts and systems might fail, and such failures will inevitably affect the productivity of the system.

Considering an autonomous vehicle, who is to make sure the vehicle is capable of doing its job? The natural answer is that a complex autonomous vehicle itself must be capable to assess its current condition, predict its future condition, and adapt its running parameters in order to maximize productivity and minimize cost.

The condition of a mining vehicle is heavily influenced by how the vehicle is operated, and by the environment around it, and this creates a need for individualized monitoring. This licentiate thesis focuses on how to utilize available sensor signals, readily available on a large amount of mining vehicles, to make assessments of the current vehicle condition. This in turn will be used both to aid in tasks such as maintenance planning, but also as an important input to decision making for the machine or planner, i.e., how to run the machine for minimum damage.

1.1 Maintenance philosophies

The field of maintenance can coarsely be divided in 3 areas. The most fundamental is reactive maintenance, where errors are fixed as they are found, also known as break down maintenance. This can be a good option for failures not causing considerable production loss or damage, like a light bulb. It is however a poor option for most components given its unpredictability, causing sudden loss of functionality and unplanned stops.

Preventive maintenance on the other hand, is when parts are exchanged based on some parameter other than failure, such as running hours of the machine. A classical example is the change of the timing belt in a car engine at set intervals. The benefits include a reduced number of unplanned stops, i.e., reduced risk of failure and secondary damage, and reduced degradation of certain components. The downsides however, is a large, potentially unnecessary, cost for parts and labor, since different individual machines do not deteriorate at the same rate.

Condition based and/or predictive maintenance is maintenance based on some measurable parameter on the individual machine. Ideally one can measure some degradation parameter, and then change the parts necessary at the most convenient time right before a failure. In this way minimum maintenance resources can be used without compromising the reliability of the system. A good review on such methods can be found in (Jardine et al., 2006). Predictive maintenance is closely related to the field of prognostics, which will be further described below.

1.2 Prognostics

The field of prognostics is defined as *"Analysis of the symptoms of faults to predict future condition and residual life within design parameters"* by the standard (ISO 13381-1:2015, E). The following definitions are shown in Figure 1.1.

The End Of Life, or t_{EOL}, is defined as the time when the damage passes a threshold. This threshold is set so that the asset is no longer deemed useful, but still hasn't reached actual failure. The Estimated Time To Failure, ETTF, is the time from the point of prediction, t_{pred}, until the estimated failure time. The Remaining Useful Life, RUL, is the time between t_{pred} and the t_{EOL}. The prognostics problem is to estimate when t_{EOL} occurs, to allow for suitable actions to avoid reaching an actual failure. The prognostics problem is twofold. First, the current damage state needs to be estimated, which is typically done using some sensory input. This is simultaneously the way to gain knowledge how certain usage connects to generated damage on the asset. Second, once at time t_{pred}, one needs to decide on how the damage will evolve. Following the latest damage rate according to A or the long term trend B are two options, generating two quite different predictions of RUL. The second part is largely dependent on the predicted use of the machine.

Prognostics relies on some measured signal from the asset, together with a

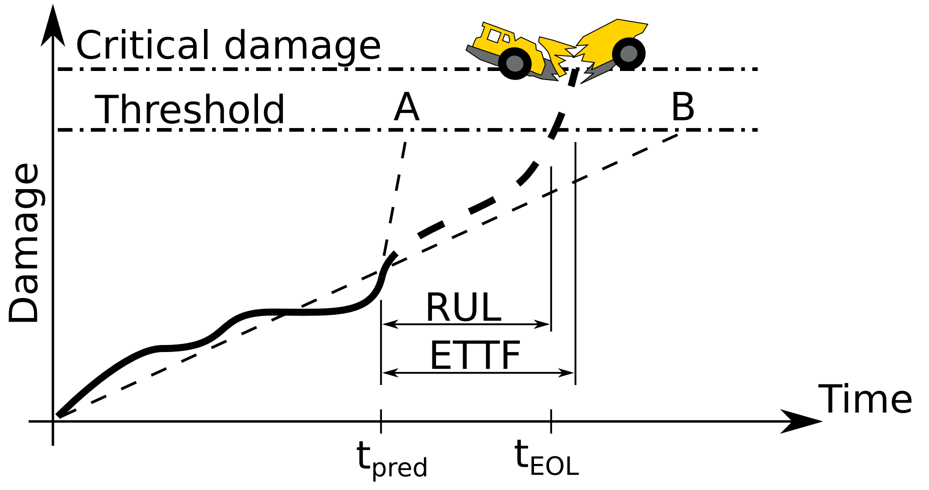

Figure 1.1: The Remaining Useful Life, RUL, is the time from the time of prediction to the End Of Life, EOL, as set by a conservative damage threshold. The Estimated Time To Failure, ETTF, is the time until the failure is predicted to occur. A and B shows two possible estimates for t_{EOL} based on the short- and longterm trend of damage respectively.

model relating said signal to a deterioration process. There are many ways to develop such models, but in principle they can be divided into three groups: experience based, physics based, and data driven approaches, (Liao and Köttig, 2014). To complicate the nomenclature slightly, the physics based approaches are often called model based, but since models in a wider sense are used in all the approaches, we stick with the term physics based when referring to models created from first order principles.

Also combinations of the three groups are possible, as defined by Liao and Köttig (2014). Using their definitions, the main work in this thesis can be categorized as: *Use a data-driven model to infer a measurement model, and use a physics-based model to predict remaining useful life.*

1.2.1 Experience based approaches

The experience based approaches are typically generated by gathering the accumulated knowledge among experts in the field into a set of if-then-else statements. Figure 1.2 shows such an approach, where an inspection combined with experience leads to a possible corrective action.

Experience based approaches can be an efficient way to transfer knowledge to a larger group of people, but relies heavily on the existence of experts within the area. The main benefits and drawbacks are listed below.

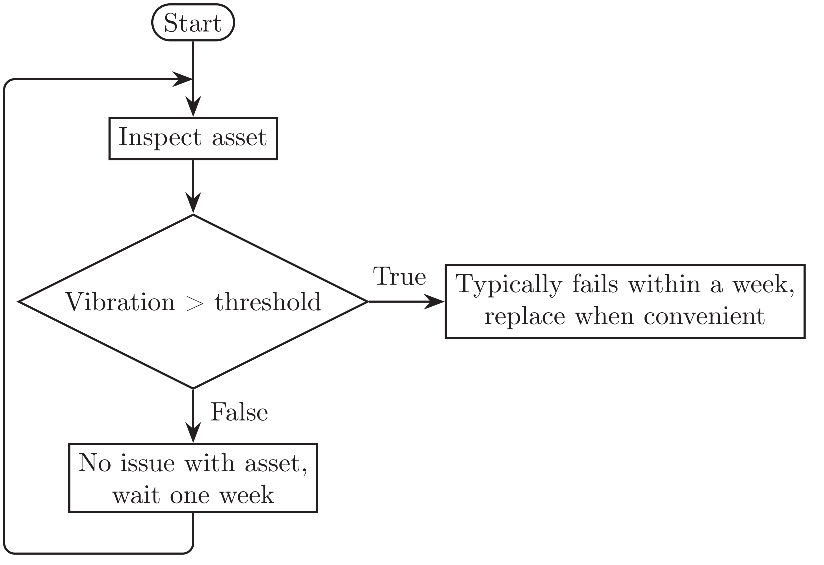

Figure 1.2: An example of a simple expert system, formalizing experience about machine condition with relation to some examined variable.

+ The rules are typically easy to understand.
+ The process is logical from a human point of view.
− There is a risk of a combinatorial explosion for complex systems, making the approach complicated even though the individual rules are easy to understand.
− It requires experts with deep system knowledge.

1.2.2 Physics based approaches

Physics based approaches are based on first order principles, and use the underlying physics to explain both the operation and the various degradation processes of a system. Benefits and drawbacks are listed below.

+ The models can be designed during the product development, though the assets might be required for parameter tuning.
+ The models incorporate physical understanding.
+ The models can be transferred between similar assets, possibly requiring new parameter tuning.
− The approach requires accurate physical models of (fast) dynamics.

– Detailed knowledge and models of (slow) degradation are needed.

– Mainly anticipated, and thus modeled, failure modes are handled. Detecting anomalies can however be done also with model based approaches.

– Model development is often hard, time consuming and thus expensive, if even possible.

– The computational burden can be high, for example when finite element modeling (FEM) or computational fluid dynamics (CFD) are used.

The physics based approaches easily become complicated, as exemplified by Daigle et al. (2012) where a small system including a pump and a motor are monitored using a physics based approach. Even for this small system, the knowledge required is substantial.

An example similar to the work in this thesis is presented by Luo et al. (2008), who describes a model based approach where fatigue estimating techniques are combined with first order models for a suspension system.

1.2.3 Data-driven approaches

Data driven models relieve the need for physical understanding, by using measurement data to find the relationships between measurable signals and damage. A good review on data driven statistical approaches is given by Si et al. (2011). Benefits and drawbacks are listed below.

+ There is no need for physical models of degradation and dynamics.

+ The approach can capture unknown failure modes.

+ The available techniques are not specific to a certain domain, i.e., the methods can be transfered to different applications. However for each new case the parameters need to be re-learned.

– Data from an operational vehicle is required. Model development can only be done after the vehicle is built and used.

– A lot of data is typically required, and also run-to-failure data, which is often expensive and in some cases dangerous to obtain. Some exceptions to this drawback exist, such as anomaly detection.

– The approach suffers from the fact that errors are rare events, leading to extremely unbalanced data sets, which are hard to learn from.

– The learned relations rarely take account of causality, i.e., directed relations between problems and symptoms.

One example of a data-driven approach from mining machinery is given by Laukka et al. (2016), who uses four accelerometers to monitor the front axle on a load-haul-dump machine. Similar to many mobile applications, the lack of a base-level operating point makes it difficult to isolate vibrations caused by axle deterioration from process vibrations.

1.3 Autonomous systems

Situational awareness is an enabler for most autonomous systems as discussed by Reichard (2004). It is also one of the main hurdles to overcome before we will see autonomous cars, domestic robots, etc. Situational awareness is often assumed synonymous with *external* situational awareness, i.e., to know your surroundings and to be able to anticipate what other agents in the system will do. We claim however, that the *internal* situational awareness is also important to realize a fully autonomous system. What point is there to know your surroundings, if your own health condition will prevent mission success? If the internal state of an asset or the possible deterioration of such state is misjudged, any planned mission is at risk to fail.

The asset condition influence an autonomous system on multiple levels. During planning of a mission, not only the current health, but also the capabilities of the asset given the current health must be known to select a feasible plan. Determining such capabilities is not an easy task, and remain an unsolved problem according to Angulo Bahón et al. (2007). A worn asset might not have the same performance, speed, battery capacity, or ability to handle high load etc. In an industrial setting, completing the mission is normally not the only target. Moving a rock from point A to B should not only be performed, but it should be done as effectively as possible. This puts further demands on the mission planner, where the asset health should not only be taken into account to allow the mission to be completed, but the mission planner should also balance the cost for deterioration of the asset with the gain from production to maximize overall profit. Allowing time for maintenance is another crucial task for the mission planner that needs to be addressed.

During mission execution, the health state of the asset will act as a monitor of unforeseen events. Sudden damage on the asset by external factors could limit performance, and may require the mission planner to re-evaluate the effectiveness of the plan.

The system becomes even more complicated as multiple assets, with different health states, can be chosen for the same mission. Should the truck A with a RUL of two days really be used for a critical mission in the mine, or is it better to wait for truck B with RUL of 1 month to be available? Risk assessment becomes an important task as the vehicle health state is taken into account. An example of this, applied on battery management, is shown by Berenz et al. (2012).

1.3.1 Mining

Some features of mines put special requirements on the prognostic solutions. Such features are discussed in this section, highlighting important differences to, for example, common road vehicles. The vast majority of vehicles in the world are designed for use either on roads or on open surfaces, such as fields or construction sites. Such environments are very similar around the world. Roads are roughly the same sizes, and hence the vehicles designed for roads can be manufactured in huge series with hundreds of thousand of units.

For the underground mining industry, the picture is quite different. An underground mine is designed around its ore body, which in turn is shaped from geological processes millions of years back. Figure 1.3 shows a typical layout of an underground mine, where the infrastructure size and layout is a direct result of the existing ore body. This results in large differences between different mine sites around the world, and not one mine is identical to another. For a mine to be profitable, the ore needs to be extracted in a cost efficient way, and this typically means removing as little unnecessary material as possible. This becomes increasingly important as mines tend to go deeper and deeper as the shallow ore deposits in the world depletes. Other parameters such as rock quality and rock pressure due to depth also puts limitations on the sizes and shapes of the drifts and tunnels in the mine.

The implications from a prognostics perspective are that the vehicles in mines around the world come in a large variety of sizes, shapes, and customization levels. Tunnel cross sections vary, and typically one wants vehicles as large as possible to maximize productivity, but obviously still having room in the tunnels. Figure 1.4 shows a small subset from the large variety of vehicles operating in mines around the world. Even for vehicles doing the exact same task, such as drilling a hole or moving material, there are many varieties such as extra low vehicles, extra narrow vehicles, etc.

Ever changing environmental laws and different technological levels of different customers results in even more varieties and customization of the vehicles. Hence mining vehicles are made in small series, with a high customization level compared to the automotive industry. Many mining vehicles also have a long life span, and can face multiple rebuilds and upgrades before reaching their economical end of life. This naturally has an implication regarding the types of prognostic methods that are suitable, and also on the economics, i.e., how many vehicles will share the burden of developing a prognostics solution.

A number of imminent changes in the mining world could potentially affect the need for prognostic solution, and hence justify development despite small series. One such change is automation, where internal system awareness becomes a necessity and not only a mean to reduce maintenance costs. A second change is the drive towards a service based cost model, where equipment manufacturers sell the service performed rather than the equipment performing it. With such a setup, the need for monitoring increases since the usage needs to be connected to the costs charged to the customer.

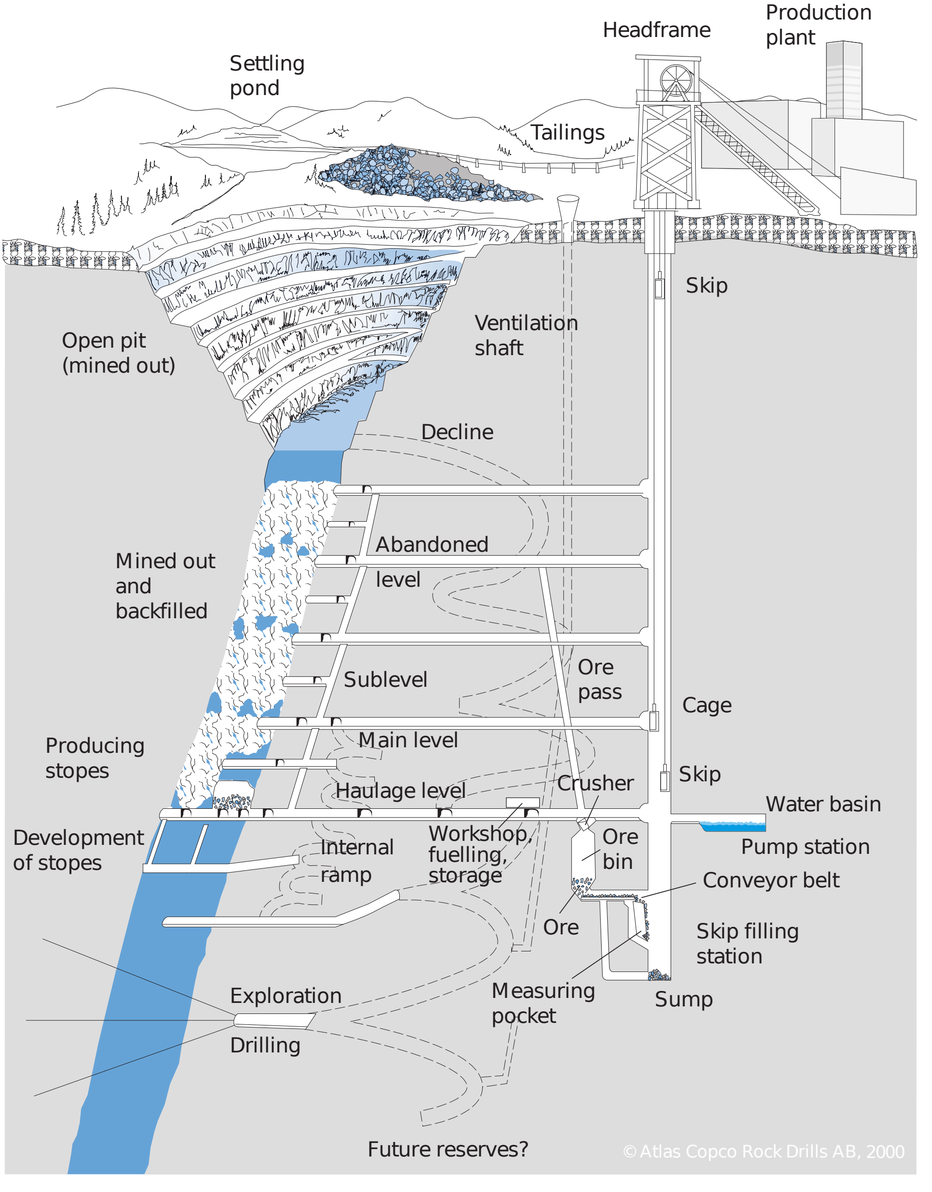

Figure 1.3: A typical underground mine is designed around its ore body. Numerous mining methods, depths, regulations, and practices results in a need for a large variety of highly specialized vehicles. This in turn results in small series of each particular vehicle type, which affects the opportunities for prognostic applications.

1.4 The vehicle

The underlying methods presented in this thesis are applicable to a wide range of mining and construction vehicles. Given the availability of data, the particular vehicle used to develop and verify the methods is the Epiroc mine truck MT65 as seen on the cover of this thesis. Depending on the mining method, the tasks of mine trucks differ. In some mines, the mine trucks are the main transport of ore, all the way from the bottom of the mine to the surface. In such mines, one cycle from loading to unloading and driving back can last for hours. In other mines, the mine truck is primarily used for transporting material short distances between a producing stope as seen in Figure 1.3 and some ore pass or crusher. Some other equipment such as a train or skip (mine elevator) is then used to transport the ore to the surface. In some particular cases, the transport of material is even downhill due to either a high location of the ore body, or the use of left over materials to back fill a mine for stability. Whether the machine travels uphill or downhill, for minutes or hours, and with few or many changes of load, naturally effects the durability of the vehicle, enhancing the need for individualized monitoring. For a given mine however, there is often some possibility to predict the usage of the mine truck, since the mining method rarely change. This can have positive implications when considering prognostics, since the uncertainty about usage can be reduced and a better prediction can be made. Table 1.1 gives a brief summary of the properties of the studied vehicle.

Table 1.1: Basic data for the MT65. Source: (Epiroc, 2018)

Property	Value
Load capacity	65,000 kg
Dumping time	13 s
Approximate weight	46,300 kg
Front axle load	33,600 kg
Rear axle load	12,700 kg
Power rating	567 kW
Length	11,021 mm
Height	2,985 mm
Width	3,500 mm

Figure 1.4: Examples of different mining machinery for drilling, loading, hauling, reinforcing, concrete spraying, etc, together with multiple sizes and types to accommodate for the different needs of different mine sites. Asset: Epiroc

Table 1.2: Measurement equipment used

Hardware	**Use**
NI cRIO 9104	FPGA chassis, connecting the different DAQ units
NI cRIO 9014	Realtime controller
DAQ NI 9239	Data acquisition for velocity and pressure sensors
DAQ NI 9236	Data acquisition for strain gauges
DAQ NI 9234	Data acquisition for accelerometers
KYOWA KFG-5-350-C1	Strain gauge type used
PCB M356B08	Accelerometer type used
Kvaser Memorator	CAN datalogger

1.4.1 The measurement project

Several of the papers included in this thesis shares data from a large measurement project performed at a number of mine sites. The main objective of the measurement project is to verify the Finite Element Analysis (FEA) that is used to design the strength and fatigue properties during vehicle development.

The main query of the measurement project is whether the fatigue calculations performed and the distribution of loads corresponds to the real fatigue and load distributions in a live field application. To do so, a large number of strain gauges and accelerometers, typically too costly and fragile for reliable use in operation, are mounted on two prototype machines. After some calibration procedures in a test mine, the machines including measurement systems are sent to two different mine sites for use in real mine production.

To verify system performance also other parameters, not directly linked to the fatigue investigation, are monitored. This includes all data available on the vehicle CAN-BUS system which includes data such as payload, engine data, gear box speeds, suspension lengths, operator inputs, control outputs, and various temperatures. Worth mentioning is that none of the available signals are present for reasons linked to condition monitoring or prognostics.

Measuring strain requires carefully assembled sensors, firmly attached to the metal surface of interest. This is typically done by cleaning the measurement object down to the metallic clean surface, and then to glue a strain gage to the surface. The gage needs to be protected from the environment, given its sensitivity to moisture and mechanical abuse. This is also true for the cabling from the sensor to the data acquisition unit. One such installation is shown in Figure 1.5 (d). The installation process makes the strain measurements tedious and expensive. Accelerometers as seen in Figure 1.5 (c) are less sensitive to both abuse and moisture. Good metallic contact is however necessary to avoid damping between the measurement object and the sensor, especially for high bandwidth measurements. Figure 1.5 and Table 1.2 summarizes the equipment and vehicle used in the measurement project.

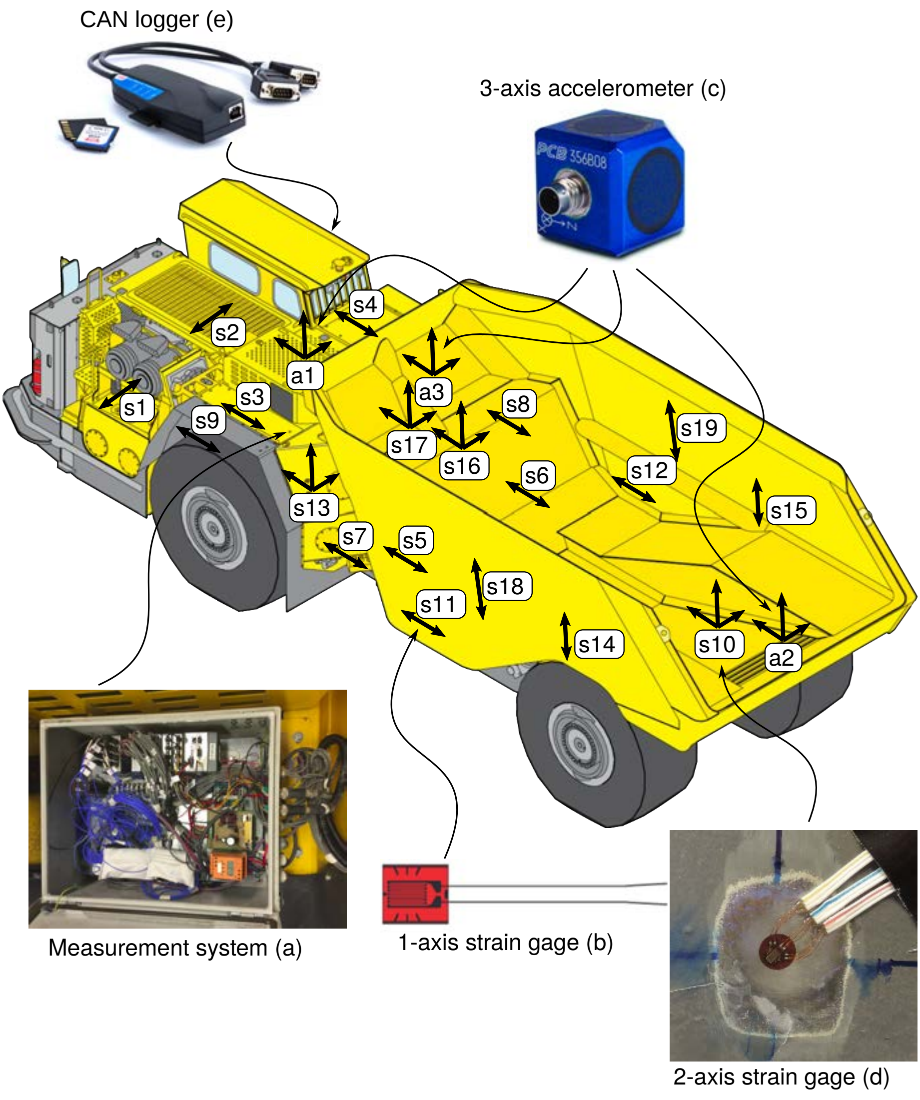

Figure 1.5: A summarizing picture of the measurement project showing: The vehicle including all strain gauge positions (shown with an arrow in the measured direction), the measurement system (a), one of many identical strain gauges (b), the accelerometers used (c), a typical strain gauge installation (d), and the CAN logger (e).

1.5 Motivation

The work in this thesis is concentrated on the vehicle frame for a number of reasons. The frame is the main component of the vehicle, and frame damage is a key indicator to how the machine is used. It is also the component that limits the overall life of the machine to a large extent, since other components are commonly exchanged during the vehicles life cycle. Once the frame is beyond repair however, the machine is considered to have reached its end of life. The frame is also a good example for the difficulties of available prognostic approaches, incorporating both large Finite Element Models, but also long degradation times prohibiting data-driven approaches.

Physics based approaches can be complicated, and result in large, computationally intensive models. A typical Finite Element Model can take hours to evaluate on specialized computation hardware. This is typically not feasible or at least not cost effective for use on data from many individual machines. Simpler models with less fidelity and shorter computational times are required.

Vehicle deterioration is typically a very slow process. Using pure data driven approaches require good operational data, and typically also run-to-failure data under real operating conditions. Taking as an example the vehicle frame, with a designed life of up to 30,000 hours, the process of collecting data thus becomes infeasible. Given the intention to deliver a prognostic solution together with a newly developed vehicle, a data driven approach learning from failure data is not a viable option. The slow deterioration process is particularly problematic for long duration vehicle components, that share little between generations and vehicle models, such as frames.

Our approach is instead to use data for generating a model, and to then use a model based approach, where known damage physics are used for the actual prediction. In this way, we can utilize the data from either a prototype or a simulation, and obtain models describing wear early, already in the prototyping stage. Ability to deliver a wear model upon delivery of the vehicle to a customer is crucial if we wish to use the rate of deterioration of the vehicle as input to the decisions how to operate the, possibly autonomous, machines.

1.6 Research questions

While applied on a particular vehicle due to data availability, the research questions (RQ) are general both within and outside the mining domain.

RQ1: What level of complexity is required of a model in order to be used for prognostic purposes?

RQ2: How can available sensors, not intended for prognostics, be utilized to predict the current condition of a mechanical frame without the need of detailed system knowledge?

RQ3: How can acceleration sensors be used to categorize what task a machine is performing, and thus aid in predicting the usage and wear of said machine?

RQ4: How can condition monitoring be utilized in a larger setting, such as the overall planning of the mine?

1.7 Contributions

The main contributions for the individual papers are summarized in this section. Unless otherwise is explicitly stated, the author has contributed with the majority of research work, presentation, and analysis work.

Paper I: Data driven modeling and estimation of accumulated damage in mining vehicles using on-board sensors

The main contribution of this paper is the result that input from general purpose sensors such as accelerometers, gyroscopes, and pressure sensors combined with a linear model is sufficient for estimating accumulated damage on a mining vehicle. We further show a number of signal selection techniques to reduce the amount of input signals, and to find at what location strain can be estimated from the given sensors. A final contribution is the results that accumulated damage can be used as a road monitoring system.

Paper II: Fatigue Damage Monitoring for Mining Vehicles using Data Driven Models

This paper continues the work from Paper I, but changes the scope to include only the standard sensors on the vehicle. Contributions include that a model-free approach in insufficient to capture the accumulated damage, but that a low order linear model can recreate most of the dynamics found in the stress signal. We further explore the different driving tasks of the vehicle, with the contribution that accumulated damage calculated from standard sensors and a linear model can be used in a prognostic setting, and give insights on differences between operator behavior.

Paper III: Automated Usage Characterization of Mining Vehicles For Life Time Prediction

In this paper, the idea of characterizing the tasks of the vehicle is brought further. Instead of focusing on the high-end computerized vehicles, we aim to create a monitoring system for the simplest machines, i.e., machines with almost no sensors. Contributions include how well systems used for Human Activity Recognition work for detecting vehicle tasks. In particular a system using a single accelerometer together with a convolutional neural network, that is trained to recognize acceleration patterns during different tasks is presented. We further show that our approach is able to distinguish 5 different classes with 96% accuracy on a balanced test set.

Paper IV: A System for Underground Road Condition Monitoring

This paper presents a combination of systems, where localization, road monitoring and mine planning are integrated. We show that an underground vehicle can be localized using readily available sensors such as Inertial Measurement Units and Wifi access point signal strength. With a known position, we can deliver road condition data to the central planning system and enable low-invasive re-planning procedures to allow for road maintenance work to be performed.

This work was conducted as a joint project between several companies and universities in the WASP project. The contributions made by the author covers the road monitoring section, the modeling and simulation of the quarter car, and the Power Spectral Density estimations, but not the localization nor the planning.

1.8 Future vision

From the perspective of the system provider, i.e., the company building machines to be shipped together with a prognostic solution, a number of fundamental problems remain unsolved. Especially in the case where the condition monitoring and prognostics are used as inputs to an autonomous system mission planner.

The first problem is the time aspect of model development. The prognostic model needs to be ready when the product is ready. For data driven approaches this is a fundamental contradiction, since they also need the product to generate the data, which is difficult to combine. Three possible solutions are seen by the author. Either there is a simulation model good enough to generate the data needed, though one can then argue why we would need the data-driven approach at all. Or, there is some effective way to transfer learned models from similar products, and only needing a tiny bit of data from the newly developed vehicle. Finally, one can imagine some sort of hybrid model, where a data-driven approach is combined with physics based models in such a way that the system learns how to use physics based degradation knowledge.

For physics based approaches, one can argue that the time and work it takes to create the physics based model prohibits the possibility to ship a prognostics solution together with the product, but at least no fundamental contradiction is present. This leads up to the second issue, especially considering the mining application, namely cost.

The second problem is the cost of prognostic solutions. A prognostic solution must be cheap enough to be worth while. In the mining setting, this is a serious problem since many prognostics methods target one particular type of machine. Given the small series and high customization in mining, few vehicles of each type will share the burden of developing a customized prognostics solution.

A mining vehicle, though highly specialized, typically consists of a large number of standard components and subsystems such as hydraulic pumps, engines, gearboxes, batteries, hoses, drive trains, etc. A reasonable solution could be that each such subsystem manufacturer delivers prognostic solutions that are easily integrated in the overall system. In this way the number of units sharing the development cost can be increased substantially.

This leaves a number of research areas particularly interesting to make prognostics fly in the mining industry, and also generally across many industries:

- Integration of multiple subsystems, each with their own prognostic solutions, in a cost efficient way.
- Research on transfer learning, where models and data from previous models and types can be re-used to quickly and cheaply create prognostic solutions for future vehicles.
- Research on the unique components not available in other industries, nor from sub-suppliers. Such components include frames, breakers, and rock drills.
- Reduced order models, where some of the downsides of Finite Element Models are removed by simplifying the models.

The prognostics field is still young in many aspects, and especially so for the mining industry. It is possible that the future will show that the only viable way to deliver a well working prognostics solution is to merge a multitude of model based solutions for each and every critical component of the mobile asset. Until so proven, research may continue.

Chapter 2

Rain flow counting and accumulated damage

This chapter gives a brief background to the connection between stress cycles and fatigue, i.e., the deterioration process used to connect short term measurement signals to long term damage in a material.

When applying a stress σ, a force per area, to a material, it is stretched causing a strain ϵ. The strain is a unit less quantity describing the relative change of length, typically expressed in mm/m. Applying a too large stress causes the material to fail instantly, and this stress limit is called the ultimate tensile stress, σ_{ut}. Metallic materials can however fail also for stress levels smaller than σ_{ut}, given that the stress is varying over time. This is commonly known as fatigue, and is due to crack initiation and subsequent crack growth within the material as it is stretched and compressed repeatedly.

The common method to characterize how resistant a material is to fatigue, is to apply a constant amplitude stress oscillation to a sample in a controlled laboratory environment, and to measure the number of cycles the sample withstands before failing. This is done for a large number of samples at different stress levels, and the results are typically presented as a Stress-Cycle, SN, or Wöhler's curve, as seen in Figure 2.1. A more thorough description can be found in (Klesnil and Lukác, 1992). The SN-curve describes how many stress cycles a material can withstand at a given stress amplitude. For a typical elastic region of a metallic material, the SN-curve can be approximated as a straight line when plotted in a log-log diagram.

When the material is later on used in a product, such as a mining vehicle, the load rarely consist of constant amplitude stress but rather a stochastic change of loads of varying amplitudes. Rain flow counting was introduced by Matsuishi and Endo (1968) to account for such load time series. The rain flow counting algorithm is named from a comparison by the original author to the way water drops travel on a Japanese pagoda roof. What the algorithm does is to count all different stress-relief cycles, present in the time series. The example in

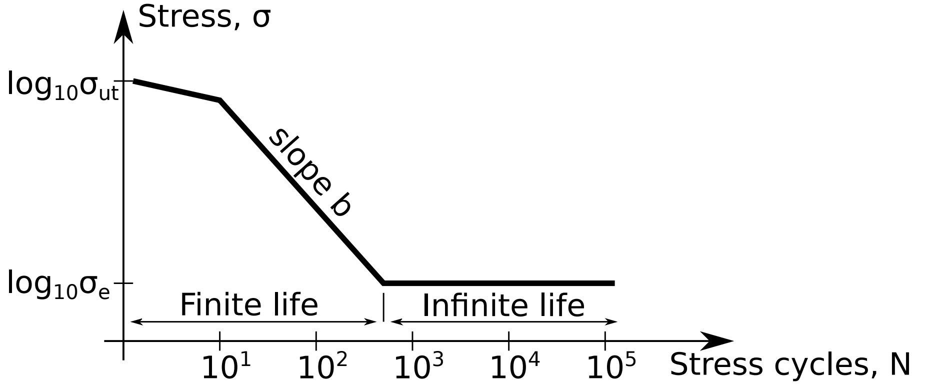

Figure 2.1: A typical SN-curve for steel, describing the relation between number of cycles the material can endure at different stress level.

Figure 2.2 shows both how the rain flow cycles occur, and how this corresponds to stress-relief cycles in the material.

The rain flow analogy is described as follows. First tilt Figure 2.2 90 degrees clockwise, and imagine the time-stress curve as a pagoda roof, allowing water drops to flow downwards along the different parts of the roof, illustrated by dashed lines. Let every point in the time series where the derivative is zero represent a maximum or minimum point. Let a new flow start at every such point starting from the top. Let each flow continue until one of the following conditions occurs:

– It passes an opposing larger maximum (or smaller minimum). This is exemplified by the flow originating at B. As the water falls off peak C, the flow stops since the magnitude of peak D is larger than peak C.

– It reaches a previous flow falling from above, like the flow originating from C, stopping at B'

– It falls below the roof, like the flows originating from A and D.

The resulting cycles from the rain flow between AD, BC, CB', DE, corresponds to the different stress-relief cycles seen on the right hand side of Figure 2.2. The cycles are finally combined into the complete hysteresis loops A-D-E and B-C-B'.

The SN-curve summarizes the experimental results for how many cycles a material can tolerate before failure. An important observation for the use in this thesis, is how large amplitude cycles dominate the damage, since the slope on the SN-curve for steel typically shows a cubic relation between stress range and damage. This corresponds to a slope $b = -3$ in Figure 2.1. A small error in estimating a large stress range can thus have a larger implication on the final damage, than a large error for smaller stress ranges.

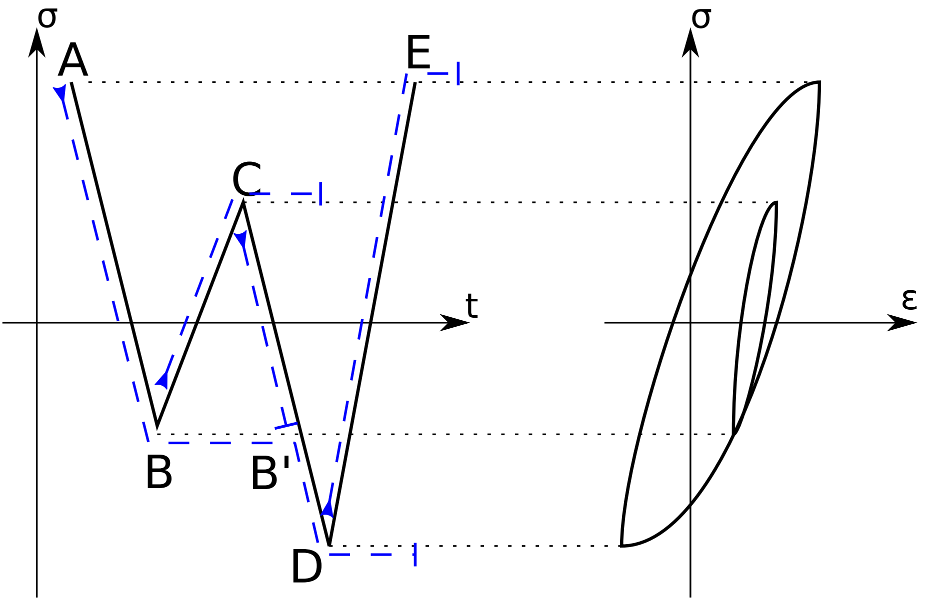

Figure 2.2: An illustration of the rain flow counting algorithm in a stress-time plot (left) and the corresponding stress-relief cycles in the material shown as the relation between stress σ and strain ϵ (right).

A damage model is used to summarize the damage caused by the different stress cycles. The most widely used damage model is the Palmgren-Miner model, (Palmgren, 1924), where each cycle contributes a damage calculated from the SN-curve. The damage D for all cycles is given by

$$D = \sum_{i=1}^{N} \frac{1}{\mathrm{SN}(\sigma_i)} \tag{2.1}$$

where σ_i is the stress amplitude for cycle i and $\mathrm{SN}(\sigma_i)$ is the number of cycles the material can tolerate at stress amplitude σ_i. In other words, if the material is subject to one cycle with an amplitude where it can endure for example 1000 cycles, it has consumed 1/1000's of its fatigue life. The contributions from all N cycles are summed to the accumulated damage D.

There exists a number of alternative methods to rain flow counting. Most notable are the frequency based methods, who links the Power Spectral Density (PSD) of a stress-time signal directly to fatigue damage. Such methods are typically derived from the rain flow counting method, and often contain a number of parameters of empirical origin. Most common is the Dirlik method, (Dirlik, 1985). When the time history is available, the Rain Flow Count is the most common method, and hence it is used throughout this thesis.

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Papers

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