systems to collect and merge vehicle sensors' data that could be used to optimize maintenance. Having all the different sensors even from different trains linked together, as it is the approach of today's Internet of Things, a huge amount of data is created every day and needs proper analysis to discover maintenance relevant problems or tear and wear issues. More precise information on the train's condition is expected that would allow for optimized, predictive maintenance strategies based on actual needs. Unless there is a consistent and plausible model of the collected data to draw adequate conclusions, it is difficult to make use of the data in everyday business and to develop adequate maintenance strategies.

In the context of automated transit systems the use of onboard sensors becomes even from important compared to manually operated trains. While a driver may be able to note certain unusual behavior of "his" train, e.g. insufficient braking, insufficient engine power, unusual noise, long door closing times, insufficient performance of HVAC system or simply all kinds of irregularities which the well-trained human perception can feel, this is not possible for technical systems. Unless there is a sensor for a specific component to supervise, e.g. electric current meter for a door propulsion system, the potential failure may not be detected beforehand. However, putting a number of low-cost sensor IoT sensors onboard the train may help to detect unusual states, degradation issues or non-compliance of components (see Figure 2). Those sensor are the "digital eyes and ears" of the train and may compensate the cognitive skills of human drivers. Those sensors may therefore help reduce train failure, indicate potential faults and recommend maintenance actions of extend the time between maintenance actions.

CONCEPTUAL APPROACH OF BIG DATA

Nowadays, data can originate from all kinds of sources and is available in all kinds of formats. Most technical devices, may it be privately used smartphones or large and comprehensive control systems of industrial application generate huge amounts of logging data every day. This kind of data may be simple measurement values from single sensor, to capture the temperature or more complex sensor to log a GPS-based position of even more complex data such as images or video streams. Most people or and companies that collect these date anticipate the potential to generate additional benefit for their business by analyzing this data.

There is a large variety of terms and concepts around Big Data although a general and agreed framework is still missing. Different definitions exist such as „huge volume of structured and unstructured data, which is difficult to handle with conventional methods of storage and analysis. Most data originate from many different sources and are generated in real time (Hamel, 2013).

However, there are some keywords which are often used in conjunction with Big Data and the analysis of large unsorted data sets:

- **Value**: Perform an analysis on the available data to get a commercial benefit from the collected data, e.g. by cutting cost or increase revenue
- **Velocity**: Perform this analysis on a comprehensive (if possible on a complete) base in a comparably short time
- **Veracity**: Get confidence in the analyzed data and deal with a certain level of uncertainty of the data (improve data quality)
- **Variety**: Perform analysis on structured as well as unstructured data
- **Volume**: Collect, store, retrieve and process huge sets of data to create meaningful results of the analysis.

Big Data analyzes may be divided in to different activities which start with the collection of the data and eventually include the visualization or representation of the results to the end user (see Figure 3).

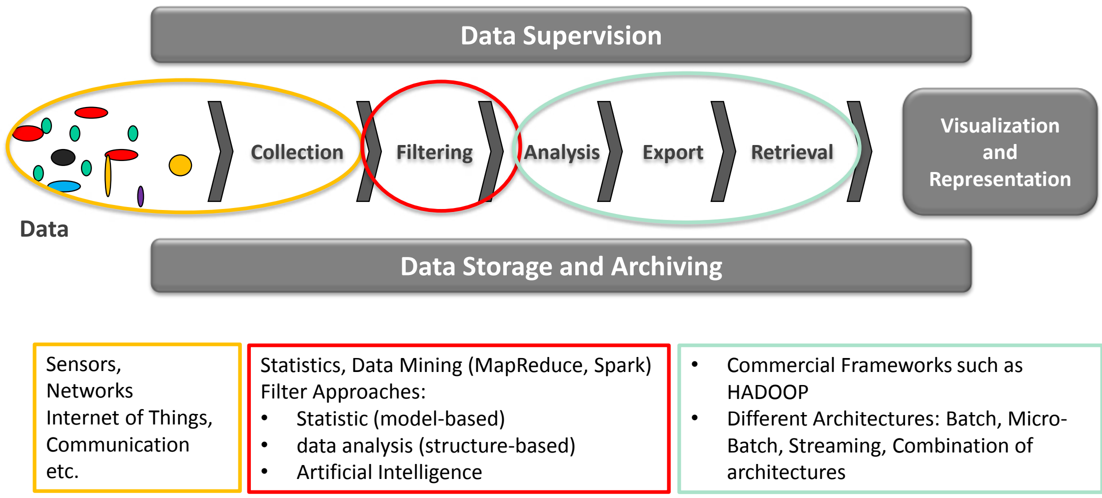

Figure 3: Major Big Data process steps (adated from Carrard, 2017)

The Internet-of-Things (IoT) can be considered as part of a large framework, i.e. Big Data, since the IoT part primarily covers the collection and transmission of data. IoT has been envisaged as supporting a large number of networked low-cost and low-bandwidth devices that are used in Machine-to-Machine communication, most often for stationary applications, such as electric meters, industrial sensor and actuators and the like. However, IoT has been an acronym for all kinds of interconnected sensor (and corresponding networks) may if be stationary of mobile and covers all kinds of applications to retrieve, collect and transmit data from such sensors. Today, it can be considered a state-of-the-art paradigm to measure and collect information of distributed systems and to make those data available, e.g. to provide an online status report of the overall system. Those data may then be used for immediate real time analysis including prompt control reactions on the system or for offline analysis with more strategic focus to improve the medium- or long-term operation of a system.

Once all data is collected the next steps is most often referred to as Data Mining (Filtering) to extract and discover implicit, unknown and potentially useful and valuable information. This paper primarily focusses on the first two aspects (data collection and data mining) and will present some results from a field test with a low-cost IoT sensor and the application of different algorithms to the collected data.

ANALYSIS OF LARGE DATA SETS

A lot of different methods to analyses large data sets have been introduced in the past. This includes different methods from the field Artificial Intelligence which learn certain pattern and try to recognize such a pattern or identify any deviation from a predefined pattern. Artificial Neural Networks or Support Vector Machines are among those classification algorithms (Najafabadi, 2015). Learning systems such as Artificial Neural Networks or Support Vector Machine can be used to learn the nominal, e.g. uncritical behavior of a system (e.g. a train). Once the Neural Networks or the Support Vector Machine is fed with status data of a faulty train, it may identify this train as faulty, since the current parameter pattern does not match the nominal pattern.

Other approaches apply Decision Trees (Rokach, 2008), Bayesian Networks (Heckerman,

1997) or Cluster Analysis (Everitt, 2011). Decision Tree are used to segment data and create a predictive model of large data sets. The rules to construct such a tree are derived inductively from existing data sets and from a tree with different decision states depending on the number of parameters that for a single data set. Potential relationships among the different parameters are modeled as If-Then-Rules at every level of the tree. Clustering of data sets tries to split large data sets into smaller once and group similar data sets together. Those data which are similar to each other are grouped into one class while other data is grouped into a second or even more classes. In case data is observed which cannot be assigned to either of the groups (clusters) this data may be of special interest for further analysis or indicate some unusual system behavior.

Apart from those more recent methods and algorithm there are many different statistical approaches to analyze data (in terms of sample) for some irregularities, similarities or statistical outliners that can also be applied to Big Data Analysis (Rettig, 2015). One of those methods is often referred to as the Kullback-Leibler-Divergence (sometimes also named Relative Entropy) and can be used to compare two random distributions P and Q of the same parameter for similarity or non-similarity, resp. (Kullback, 1951). Should this measure indicate a significant deviation of the two samples there are likely to be some systematic differences and either of the two sources, e.g. two trains, need to be inspected to discover the reason.

The Kullback-Leibler Divergence D (P||Q) is a non-symmetric measure of the loss in information. Assuming two discrete probability distributions P and Q, the Kullback-Leibler-Divergence is defined as

$$D\ \ P\,\|\,Q\ = \sum_i P(i) log \frac{P\ \ i}{Q\ \ i} \tag{1}$$

with P(i) and Q(i) being the relative frequency of the class i of the distribution P and Q resp.

$$P(i) = \frac{m_i}{\sum_k m_k} \tag{2}$$

with m_i describing the total number of elements of class i and m_a being the total number of all elements of all classes from distribution P.

The Kullback-Leibler-Divergence can measure the divergence between P and Q without any information on the type of distribution, be it Normal, Poisson or Exponential, etc. The measure itself just indicates whether P and Q are similar. D covers a range from 0 to 1 ([0; 1]) with 0 indicating a high similarity between both distributions P and Q while '1' indicates a major deviation, i.e. the 2 data sets are unlikely to characterize the same behavior of a physical parameter. For example, the acceleration rate or the jerk of a train A differs basically from that of a train B although it is the same train model, on the same track, on the same route and same time of day.

Since the Kullback-Leibler-Divergence is easy to compute and does not require extensive computing power and can handle large as well as small data sets, we have chosen this statistical measure rather than more complex Learning Algorithms for a first test of usability in the context of train state identification. More complex models and approach such as Neural Networks or Clustering are likely to be tested for usability in the future.

CASE STUDY

In order to conduct first tests and collect high level train status data a low-cost IoT sensor (XDK Data Logger) from BOSCH was used (see Figure 4).

Figure 4: IoT sensor *XDK data logger* from BOSCH (Bosch, 2017)

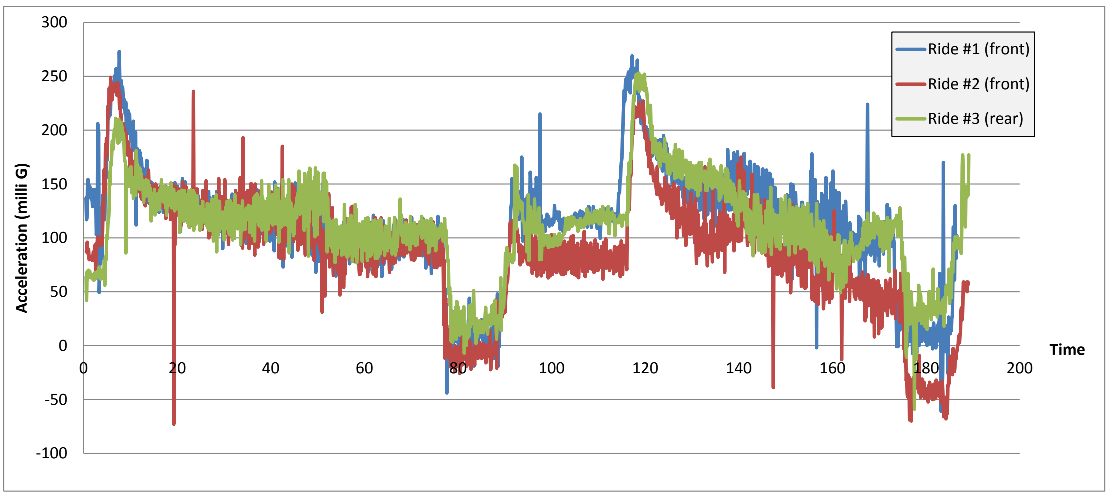

Figure 5: Recorded acceleration of the train from 3 different rides on Paris Metro (L14, Madeleine – Châtelet), Note: acceleration is noted in milli G, i.e. 200 milli G = ~ 2 m/s²

This integrated sensor comprises various interfaces, indicators and physical sensors as such. The most important features are listed below. For further reference please see (Bosch, 2017).

- Integrated sensors: accelerometer, gyroscope, magnetometer, humidity sensor, pressure sensor, temperature, acoustic sensor, light intensity sensor.
- 32-bit microcontroller ARM Cortex M3, Bluetooth, Wireless LAN, Mirco SD slot
- Push buttons, Status LEDs (programmable), debug & extension port
- Li-Ion rechargeable battery

A dedicated power supply system or connection to the onboard power system is not necessary. However a USB power bank is recommend for increasing battery lifetime of the sensor. Various interfaces provide communication on a real time or on-demand base to transmit the collected data. The tests had been conducted without using the wireless communication interfaces to save energy and increase battery lifetime. The data was collected on a day-by-day basis from the SD memory card and then transferred to the lab for further analysis.

The sensor was used on several light rail lines (city of Dresden, Germany) and subway lines (Paris Metro, France and Nuremberg Metro, Germany). During the train rides all available sensor values were recorded and used for analysis. From a ride quality point of view but also regarding the brake and acceleration performance as well as the condition of the train engine the train acceleration is considered to be very important. Therefore the analysis of the collected data focused on the recorded acceleration values.

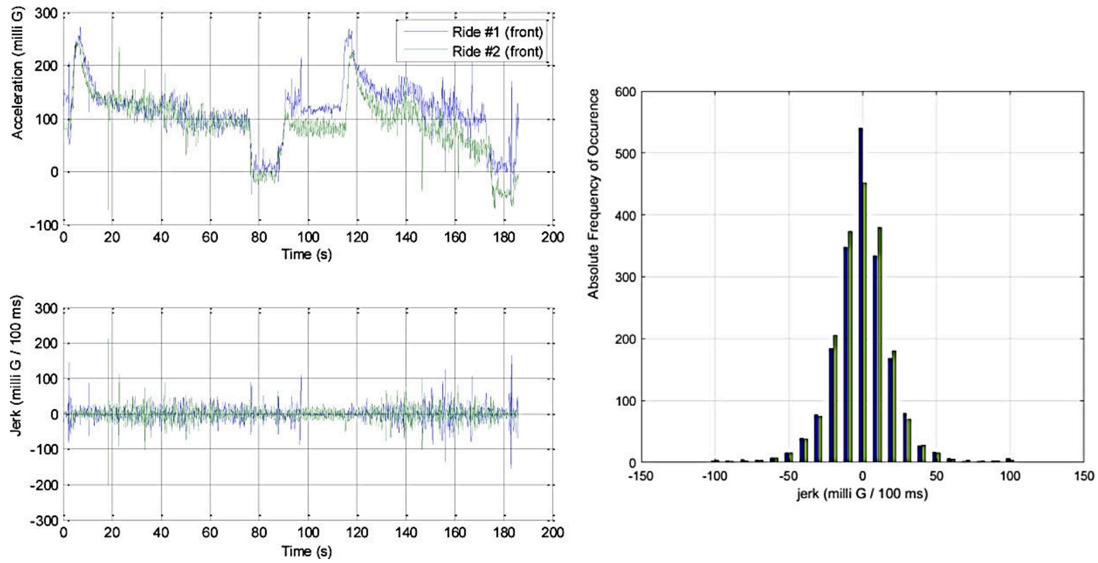

Figure 6: Acceleration profile, derived train jerk and corresponding probability distributions of two train rides

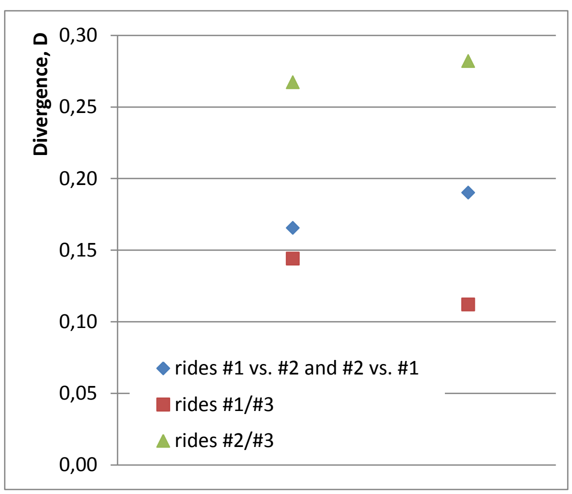

Figure 7: Calcuated Kullback-Leiber-Divergence of 3 train rides (comparing all rides with each other)

Substantial differences were recorded between the light rail and the subway systems, because of the impact of the car traffic on the light rail lines (at-grade intersections, traffic lights, sudden stops due to cars crossing the tracks, etc.). The ride profile of the subway trains was much smoother and even more coherent between different trains.

Figure 5 shows the recorded acceleration from different train rides having the sensor installed both at the front and the rear of the train set. Three different train sets were used but the route between 3 stations and the direction of travel were identical for all rides. From a human perspective all acceleration profiles seem very similar, although there are some outliers on ride #2. The absolute acceleration values differ between the rides (especially on the second section), which might be caused service requirements, e.g. faster or slower acceleration to adhere to the timetable.

To account for these (systematic) differences the jerk of the train was used rather than the acceleration. The jerk was derived from the acceleration values simply by temporal derivation of the signal (see Figure 6). The jerk value was then grouped into different classes to get the probability distribution of each train ride. As an example. Figure 6 shows the probability density distribution of two train rides.

The Kullback-Leibler-Divergence of the different train rides was then calculated comparing all rides with each other (ride 1 with rides 2 and 3, ride 2 with 3, and vice versa). Since the Kullback-Leibler-Divergence D is a non-symmetric measure, D was computed by comparing ride 1 with 2 and 2 with 1. The calculated figures delivered plausible results, indicating a Divergence D not higher than 0.3 and often smaller than 0.2. According to the definition of D this indicates that all trains show a similar jerk (and acceleration) profile. Substantial technical issues of the train may reasonably not be assumed.

CONCLUSION AND FUTURE WORK

The used sensor (Bosch XDK) proved to be viable in various situations and provided consistent data measurements. It is easy to handle and can be installed in nearly any environment onboard a train. Dedicated built-in vehicle sensors or interfaces to the onboard train control system had not been necessary for the measurement campaign.

The statistical measure Kullback-Leibler-Divergence was used to compare different distributions of the measured parameter, primarily putting focus on train acceleration and jerk. This measure is easy to compute and does not require extensive computing power and can handle large as well as small data sets. More complex models and approach such as Neural Networks or Cluster Analysis are likely to be tested for usability in the future. The existing statistical data model will be improved and consolidated to be able to issue warnings automatically.

Further physical parameters and potential interrelations among them are to be investigated to improve the diagnosis of unusual or unexpected pattern. The selected algorithm and approaches had been successfully applied to discover certain unexpected values and had also been able to classify all train free from defects. A massive data collection onboard an Innovia APM is envisaged for 2018 and shall deliver valuable measurements from the field for further development of the approach.

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Urban Maglev Operation and Maintenance—Increasing Efficiency by Applying Lean Production Principles

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ABSTRACT

To thoroughly test, a novel fully automated urban maglev people mover system a test track was designed and built at the company's headquarters in Sengenthal, Germany. Here prototype vehicles are permanently tested under commercial operation load scenarios. Special attention is paid to realistic operation and maintenance (O&M) of vehicles and guideway. In addition, system modifications where components are replaced or upgraded by new versions derived from our continuous improvement efforts and engineering test are carried out. This mix of operational modes provides a challenging complexity for O&M activities. Our group took these challenges and created substantial improvements to operational effectiveness. The paper describes the system in detail, explains the lean production methodology and tools we used to create these improvements. It also quantifies the progress that was possible by these efforts, for example, the effective availability was more than doubled. Although the vehicles run on a test track, the operational mix provides an O&M complexity comparable or even beyond commercial operated systems. Therefore, the methods and results presented in our paper can be easily transferred to commercial operated systems, which is already planned.

DESCRIPTION OF THE SYSTEM

The company Max Bögl is developing a new urban maglev people mover system called Transport System Bögl (TSB). It´s an automated guided vehicle system use for the urban traffic from five to thirty kilometer. The new urban maglev people mover system is suitable for worldwide use.

The trains built up of two or more sections. Each section is move with a system of short stator linear motors. During the drive, the vehicles hover according to the principle of electromagnetic levitation and rest on skids when stationary. The TSB consists also of a special guideway inclusive equipment, operations control technology and facility sites like stations and maintenance buildings. The maglev people mover system is highly reliable due to the redundant and independent execution of the core systems (drive, levitation, control).

A schematic description of the Transport System Bögl is represent in Figure 1.

TEST TRACK OF THE TSB

To test the Transport System Bögl a test track was built at the company´s headquarters in Sengenthal, Germany. The maglev system itself, the improvements during development and the realistic operation and maintenance are tested there.

In Figure 2 and Figure 3, you see pictures from our test track and maglev train.

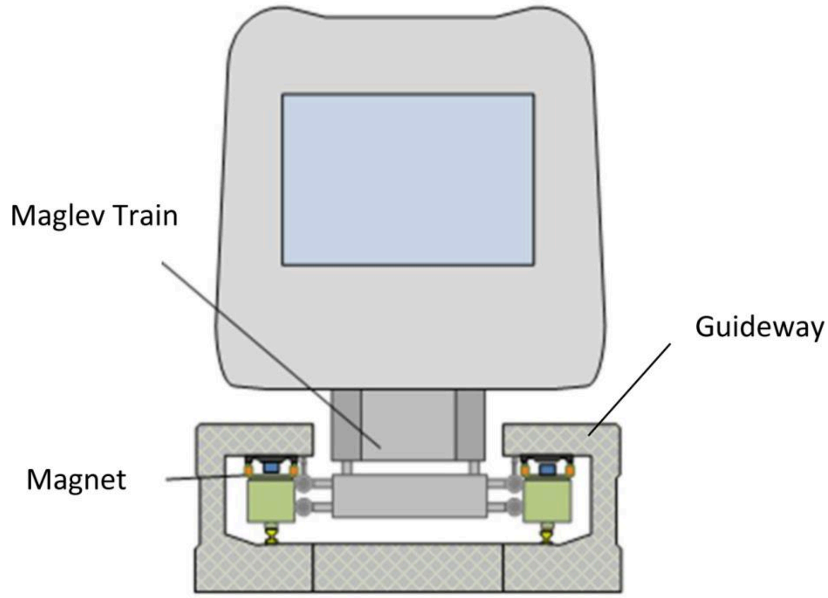

Figure 1. Description of Transport System Bögl

Figure 2. Test track at Max Bögl in Sengenthal

At this moment, the test track is round 800 meters long. Here the maglev train can drive at the maximum speed of 100 km/h. The guideway is elevated and consists mostly of concrete prefabricated compounds. A piece of the guideway is made of steel. Therefore, there are different materials for testing at our test track.

Figure 3. Maglev people mover system

Table 1. Kinds of Waste (wikipedia.org)

Waste	Explanation
Transport	Moving products that are not actually required to perform the processing
Inventory	All components, work in process, and finished product not being processed
Motion	People or equipment moving or walking more than is required to perform the processing
Waiting	Waiting for the next production step, interruptions of production during shift change
Overproduction	Production ahead of demand
Over-Processing	Resulting from poor tool or product design creating activity
Defects	the effort involved in inspecting for and fixing defects

OPERATION AT THE TEST TRACK

The operation at the test track has to be separate into three concurrent fields.