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Tools for efficient and accurate strain cycles monitoring of metallic railway bridges with wireless sensor networks

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ABSTRACT: In this paper, a wireless sensor network for strain cycle monitoring on railway bridges is presented. The network implements tools such as optimized strain sensing hardware, embedded data processing, and event driven monitoring with sentinel nodes to achieve high quality data and long operation periods. A test deployment on a railway bridge demonstrated that the monitoring system performed very reliably and the quality of the recorded data met the requirements of fatigue life assessment. Although strain cycle monitoring is data intensive and expensive in terms of power consumption, the combined use of optimized strain sensing hardware, embedded data processing and event driven monitoring allows to achieve an operation life-time of several months.

1 INTRODUCTION

The European railway network has many metallic bridges that are approaching or have even exceeded their nominal life-time (Sustainable Bridges 2004). Their safe operation beyond this life-time very often depends on the remaining fatigue life of cross beams and secondary longitudinal girders that transfer the axle forces from the sleepers to the main girders. These structural components are exposed to much more high amplitude stress cycles than the main girders. Several investigations demonstrated that monitoring strain data during operation allowed to improve the quality of fatigue life assessments of these critical structural components (Leander, Andersson et al. 2010, Bruehwiler 2015).

Typically, the monitoring program consists in acquiring strain data. Since fatigue assessment is performed by considering strain cycles induced by traffic loads, the absolute strain usually does not need to be recorded. Therefore, strain recording is only required when a train is crossing a bridge. Since such distinct events last for a short period of time, an event driven monitoring policy avoids the recording of useless data. Finally, since train traffic is highly regulated, a monitoring period of at most several months is usually sufficient to create reliable data basis for fatigue life assessment.

Among different concepts and technologies for civil structures monitoring, wireless sensor networks (WSNs) have the attractive properties of being highly automatable and cable-free, thus enabling rapid and cost-saving deployments. Reduced installation costs favor mainly short and medium term deployments which, in practice, represent the majority of monitoring applications. However, battery-operated WSNs are only competitive if they can provide good quality data and can be operated reliably and with minimal maintenance for the planned monitoring period.

Strain measurements on civil structures are usually performed with electrical resistance strain gages. While their use with tethered monitoring devices is well established, operating resistance strain gages with battery powered WSNs have an important drawback since the power consumption of resistance strain gages is very high. Furthermore, strain cycle monitoring requires a sampling rate of at least 100 Hz. WSNs are usually not designed to handle such data rates since their communication bandwidth is small and communication is very expensive in terms of power consumption. The consequences are frequent communication channel congestion with high data loss and short battery life-time.

This paper describes how tools such as optimized strain sensing hardware, embedded data processing, and event driven monitoring with sentinel nodes enable to overcome these severe drawbacks.

2 TOOLS

2.1 Strain sensing hardware

Widely deployed 120 Ohm resistance strain gages with a Wheatstone bridge as signal conditioning unit consume approximately 60 mW. This figure is comparable to the power consumption of the radio unit in transmission mode which is the most power consuming hardware component of a wireless sensor node. Therefore, operating resistance strain gages permanently implies a dramatic reduction of the operation life-time of a sensor node and frequent battery replacements.

Power consumption of strain sensing can be reduced by either increasing the resistance or reducing the input voltage of the signal conditioning circuit (Wheatstone bridge). Increasing the resistance, however, reduces the signal to noise ratio and reducing the input voltage decreases the sensitivity of the signal conditioning circuit. Therefore, both power saving methods potentially reduce the quality of data.

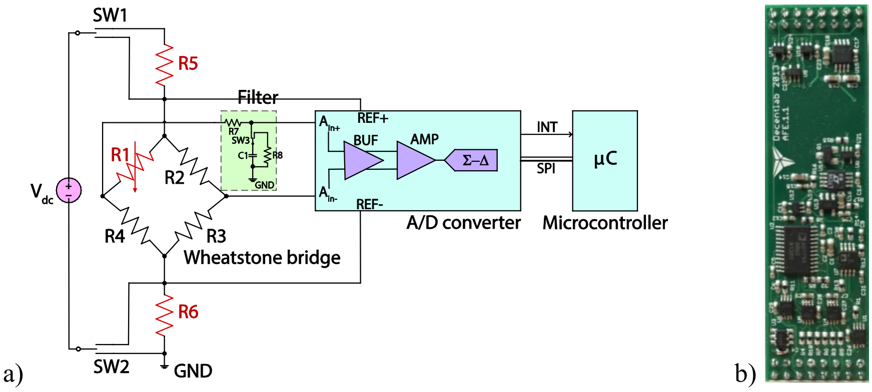

Figure 1: a) Functional block diagram of strain sensing hardware. b) Strain sensing hardware.

Both methods were implemented and tested by adding resistors in series with the Wheatstone bridge (R5 and R6 in Figure 1a) or by using 700 Ω (R1) instead of the common 120 Ω strain gages (Feltrin, Popovic et al. 2016). The strain sensing hardware (Figure 2) is endowed with a low noise A/D converter with 24 bit resolution that enables to digitalize the signal with a high resolution while keeping a good amplitude range. With the highest amplifier gain, the amplitude range is approximately ±16’900 μm/m and the resolution is smaller than 0.5 μm/m. These values comply well with the requirements of strain measurements for fatigue assessment of railway bridges which do not exceed a cycle amplitude range of 1’000 µm/m (200 MPa) and a resolution of 2–3 µm/m (0.5 MPa). The 24 bit A/D converter is slower than conventional 8 or 12 bit A/D converters since its sampling rate is limited to 470 Hz. For the addressed application, however, such a sampling rate is very unlikely to be a limitation.

Laboratory tests demonstrated that by adding two resistors of 300 Ω each, the signal noise, as expected, increases. With a 120 Ω strain gages the root mean square of signal noise doubles from 0.6 µm/m to 1.4 µm/m rms. Circuits with 700 Ω strain gages are less sensitive and achieve a signal noise of approximately 1 μm/m rms.

The power consumption of a sensor node with a conventional signal conditioning circuit and with a 120 Ω strain gauge was about 60 mW. By adding two resistors of 300 Ω each, the power consumption could be reduced to 20 mW. Replacing a 120 Ω strain gauge with a 700 Ω strain gauge produced an additional drop of the overall power consumption to 12 mW which is 20% of the standard hardware power consumption. Although this figure is still 5 time greater than the power consumption of a sensor node that is equipped with a MEMS acceleration sensor, it represents a significant operation life-time extension of a sensor node and enables permanent strain recording with monitoring periods of three weeks (Feltrin, Popovic et al. 2016).

2.2 Embedded data processing

Embedded data processing is a powerful tool for extending the life-time of sensors nodes. Power saving is achieved by reducing significantly the data communication of data intensive monitoring applications. In addition, low level data communication avoids congestions of communication channels with the benefit to diminish data loss. The feasibility and advantages of embedded data processing was successfully demonstrated in long term vibration monitoring deployments (Feltrin, Meyer et al. 2010, Feltrin, Jalsan et al. 2013).

Fatigue life monitoring by permanent strain data recording and with an embedded rainflow counting algorithm was successfully implemented and tested (O'Connor, Kim et al. 2010). In this work, embedded data processing is used to compute a sequence of local minima and maxima that represent the strain cycles exceeding a given threshold (Feltrin, Popovic et al. 2016). The algorithm works like a filter that eliminates all strain cycles that are smaller in amplitude than the specified threshold. Small amplitude cycles are very often irrelevant since in fatigue assessment methods the impact of small amplitude cycles is usually negligible. Furthermore, such a threshold eliminates also all cycles which are generated by signal noise as well.

The output of the cycle filtering algorithm can be directly used by a cycle counting algorithm (e.g. rainflow counting algorithm) to determine stress spectra. The rainflow algorithm is run on the data server. This choice keeps the embedded data processing on the sensor node simple, straightforward and more reliable. Furthermore, collecting minima and maxima of a strain history enables a better verification of the performance of the monitoring system in terms of data quality and reliability rather than stress spectra. Finally, the information provided by minima and maxima of a strain cycles time history can be used for calibrating structural models.

The functioning of the cycle filtering algorithm is illustrated in Figure 2 on a typical strain time history induced by a train on a cross beam. The original record was sampled with a sample rate of 123 Hz and consists of 1476 data points. The extremal points identified by the algorithm are plotted with markers. The cycle filtering threshold was 5 µm/m. The output of the cycle filtering algorithm consists of 34 samples. This corresponds to 2.3% of the original data size. Although significantly smaller in size, the strain cycles maps the original record with high fidelity. Such a dramatic data reduction is typical for fatigue monitoring applications on railway bridges. By keeping only the extremal points the time information is lost. However, since for fatigue assessment only the amplitude and frequency of strain cycles are of concern, the loss of time information is negligible.

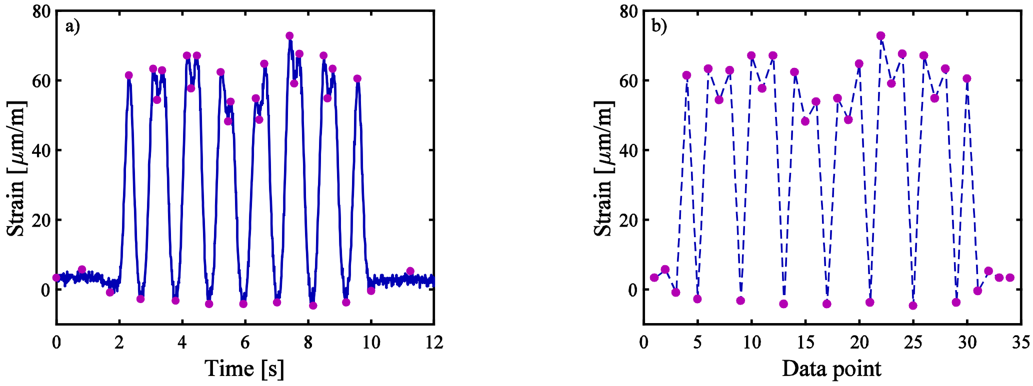

Figure 2: a) Raw data with local minima and maxima. b) Output of cycle filtering algorithm.

2.3 Event driven monitoring

Earlier implementations of event driven monitoring with a WSN for railway bridge monitoring are described in (Bischoff, Meyer et al. 2009, Feltrin, Popovic et al. 2016). In both investigations, the event identification was performed by each sensor node individually. An alternative concept is to remove the triggering mechanism from strain sensing nodes and supplementing the network with additional sensor nodes that are specialized in detecting and communicating an event to the strain sensing nodes (Popovic, Feltrin et al. 2016). The network is therefore composed by sentinel nodes, which are specialized in event detection, and monitoring nodes, which are specialized in strain sensing. Once detecting an event, a sentinel node notifies the monitoring nodes regarding the upcoming event by broadcasting alarm messages throughout the network. The monitoring nodes are operated in a power saving standby mode that is periodically interrupted by short wake ups to listen for possible alarm messages. Only upon receiving such an alarm message, the monitoring nodes will turn on their strain sensing hardware and start recording the event. After completion of recording, the monitoring nodes switch-off the strain sensing hardware, process and transmit the data, and go back to the standby mode.

This event driven monitoring concept requires that the event detection is reliable and the alarming is reliable and fast. In case that the sentinel node misses to detect an approaching train, all monitoring nodes will completely miss the event. If some of the monitoring nodes do not receive the alarming message, they will fail to capture the event. In case of a late reception of alarming messages, monitoring nodes would turn on the strain sensing hardware only when the train has partly of fully passed the measurement locations. All these cases cause data loss that bias the fatigue assessment process. Furthermore, although sentinel nodes have to operate permanently, their operation life-time has to be comparable to those of monitoring nodes.

Spreading alarming messages through a multi-hop network in a timely manner is a challenge. Since the radio device is the dominant power consumer of a sensor node it is usually operated with duty-cycling which tends to prolong message delivery. Furthermore, during the alarming, a train is between the sentinel node and the monitoring nodes. Passing trains have found to have a significant impact on the communication link quality between network nodes and can affect the reliability of message delivery (Feltrin, Popovic et al. 2016).

The alarming message protocol, which was used in this work, is sketched in Figure 3. The sentinel node creates a primary alarm message that is broadcasted to the nodes within the radio range of the sentinel node. All nodes that received the message check whether it is a new event. In this case the nodes rebroadcast the message (secondary alarm message) to their neighbouring nodes. For the purpose of increased reliability in delivering alarm messages, each node will rebroadcast message several times. The higher the number of retransmission the higher is the reliability that the alarming message is received by each monitoring node in time. However, a high retransmission number implies also a high power consumption since radio communication is very expensive.

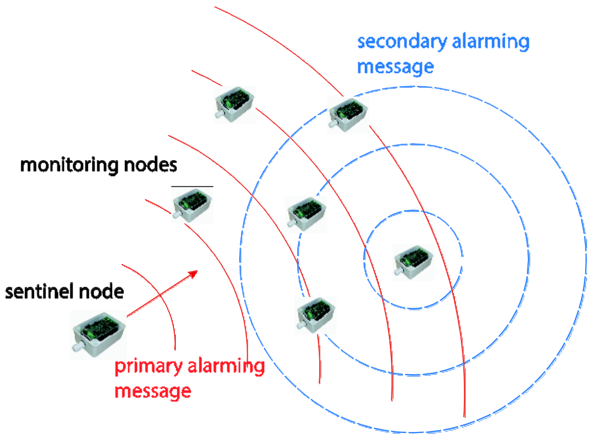

Figure 3: Alarming message protocol.

3 FIELD TESTS

The field test has been performed on a steel railway bridge that was constructed in 1946 (Figure 4a). It has a span width of 36 m and is made of two lateral longitudinal trusses which are connected with 7 cross-beams. The bridge carries one rail that is used for trains travelling in both directions. The route is mainly used by suburban trains whose speed did not exceed 80 km/h.

a)  b) 

Figure 4: a) Railway bridge. b) Acceleration sensor of the sentinel node mounted on the rail.

3.1 WSN platform

The wireless sensor network was based on the commercial sensor node of the company Decentlab GmbH (Decentlab GmbH. 2014). The core of the sensor node is the commercial ultra-low power microcontroller TI MSP430 of Texas Instrument with 256 KB of flash memory, 8 KB of RAM memory and 16 MHz CPU speed. Wireless delivery of data is performed by a low-power radio transceiver operating in European SRD Band from 863 to 870 MHz. The nominal transmission rate is 20 kbit/s. The standby mode power consumption is 0.6 µW, while during reception and transmission the consumption reaches 27.6 mW and 51 mW, respectively. The WSN nodes were operated with TinyOS2.x.

3.2 Monitoring set-up

The monitoring network consisted of 12 nodes: 2 sentinel nodes, 3 relay nodes and 6 monitoring nodes and a base station (Figure 5). Sentinel nodes are placed at a distance of about 50 m and 85 m from the bridge. The accelerometer for train detection was mounted on the rail with magnetic footings (Figure 4b). In this study, the commercial accelerometer Colibrys MS7002 was used. It has an amplitude range of ±2g and a resolution of approximately 1 mg. This low power MEMS capacitive sensor has a power consumption of less than 0.6 mW.

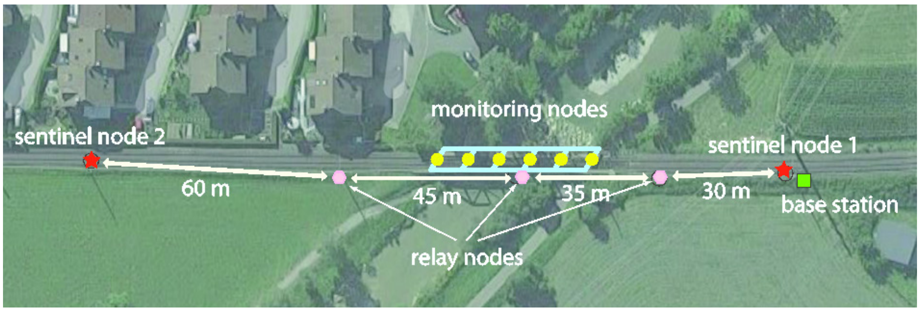

Figure 5: Monitoring set-up.

Six cross beams on the bridge were monitored with commercial strain checkers equipped with 120 Ohm strain gauges (Tokyo Sokki Kenkyujo Co. Ltd. 2005). Similarly to sensor nodes that were equipped with magnetic footings and allowed a deployment within a couple of minutes, strain gauges were hitched to the bridge using magnets (Figure 5b). They were placed in the middle of the cross-beam where the highest strain was expected.

Due to the lack of line of sight and the electromagnetically highly reflexive metallic structure of the bridge, the communication between sentinel nodes and monitoring nodes was unreliable. Therefore, three relay nodes were placed in order to create a reliable link between the monitoring nodes, sentinel nodes and the base station. All nodes were powered with two type-D batteries that provided 1.8Ah at 3 V.

The base station collected all the data of the local monitoring network and forwarded the data to a remote server via GSM. It had an average power consumption of 250 mW and was therefore powered with a car battery with a capacity of 78Ah at 12 V.

3.3 Operation mode

The sentinel nodes recorded rail vibrations permanently with a sampling rate of 123 Hz. The acquisition period for a single buffer was 0.2 seconds. The acquired data was continuously analysed by embedded data processing and compared against a threshold of 7 mg. Threshold exceedance in two consecutive buffers generated an alarm message. The alarming message was transmitted 3 times by each node.

After receiving the alarm message and switching on the strain sensing hardware a monitoring node waited 0.6 seconds before starting data collection. This delay was implemented to avoid the initial signal bias due to heating of strain gauges and charging of capacitors in filter circuits. Strain was then recorded with a sampling rate of 123 Hz for 9 seconds. Data were organized in alternating data buffers with a size of 384 samples which correspond to roughly 3 seconds of measurements. While one buffer was filled with new data, the buffer with previously recorded data was forwarded to the embedded data processing pipeline. The cycle filter threshold was set to a strain amplitude of 5 µm/m which is much greater than the noise level and corresponds to a stress of 1 MPa. The result was then forwarded to the radio for transmission to the base station. In addition, all nodes reported periodically battery voltage, information about alarming such as time of arrival and number of hops and data regarding link quality and routing of data packets.

3.4 Results

3.4.1 Strain data

An unprocessed record acquired on a cross beam with a sensor node is shown in Figure 6a). The strain cycles induced by the 4 train axles are clearly distinguishable. The record demonstrates that the signal quality is good. In fact, the noise is approximately 1 µm/m rms. A typical example of processed data provided by the monitoring system is displayed in Figure 6b). In the cycles pattern the 4 train axles are clearly distinguishable. With a filter threshold of 5 µm/m (corresponds to 1 MPa) the average data size sent over the radio was 9% of the original raw data size. By increasing the filter threshold, the many small amplitude cycles in front and rear of the main cycles, which are due to vibrations, could be removed with the beneficial effect to further reduce the data size sent over the radio.

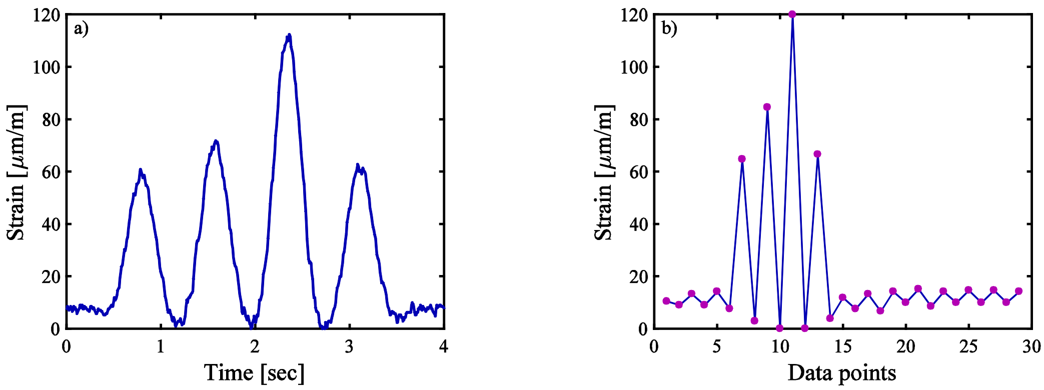

Figure 6: a) Raw data record. b) Output of cycle filtering algorithm.

3.4.2 Alarming speed

The histogram of alarm delivery period is depicted in Figure 7a. The alarm delivery period is the period between alarm dispatch by a sentinel node and alarm reception by a monitoring node. The median (50% quantile) alarm delivery period was 0.13 s and the 99.9% quantile was 0.45 s. By considering the time delay of 0.6 s for starting data acquisition after receiving the alarm message a monitoring node is ready after approximately 1.1 second. At a speed of 80 km/h, the train needed approximately 2 seconds to reach the bridge if we assume that the alarm message was sent when the front of the train reached the location of the sentinel node. Therefore, message delivery was always in time.

Figure 7b) shows the histogram of the hop distance, e.g. number of hops alarm messages did until delivery. A distance of one hop means that a monitoring node received the primary alarming message of the sentinel node. A hop distance of 2 and more means that monitoring nodes received secondary alarm messages. Primary messages have a share of 22%. This modest share is due to fact that there is no line of sight between sentinel and monitoring nodes. Relay nodes, which had a line of sight to both sentinel nodes, had a share of primary messages of 50%. The median (50% quantile) of the hop distance of monitoring nodes was 3. Nevertheless, alarm delivery was still sufficiently fast.

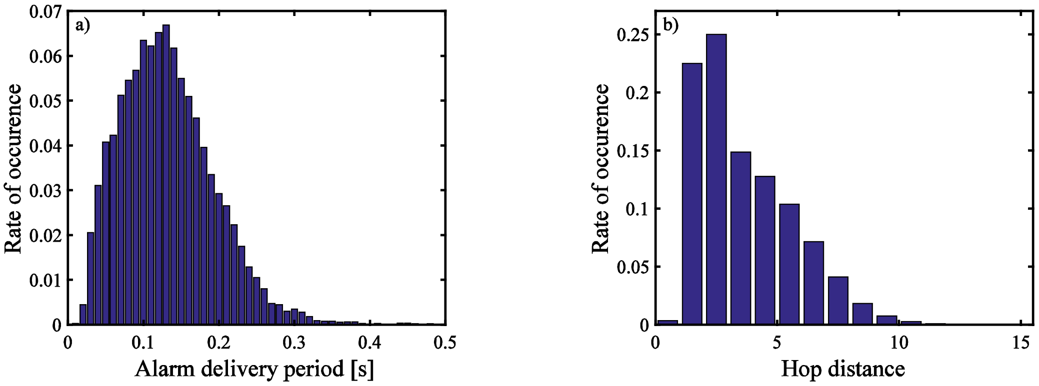

Figure 7: a) Histogram of occurrence rate of delivery period of alarming messages. b) Histogram of occurrence rate of number of hops of alarming messages until delivery.

3.4.3 Event hit rate

The number of events occurring during the monitoring period was 3728. Data of 12 of these events (0.3%) have been completely lost. Since the event identification numbers originated by the sentinel nodes have gaps, authors presume that the sentinel nodes and the network were working correctly but the data was lost either by the base station or the server.

Figure 8 shows the histogram of the number of monitoring nodes receiving an alarm message at the events. It demonstrates that in 3678 events (98.7%) all monitoring nodes received an alarm message. The total number of incomplete events, these are events that there is no data of at least one monitoring node, is 39 (1.1%).This results indicates that the success rate of the alarming message protocol was better than 99.3%.

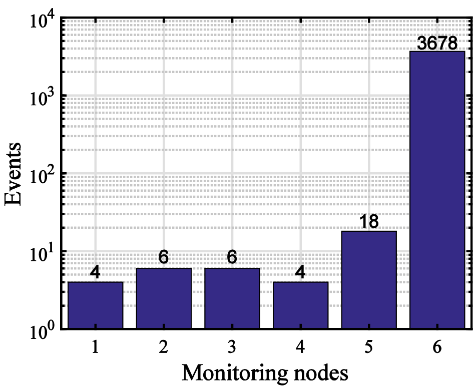

Figure 8: Histogram of the number of monitoring nodes receiving an alarm message.

3.4.4 Power consumption

Figure 9 shows the time history of battery voltage of sentinel and monitoring nodes. Power consumption induces a decrease of battery voltage with time. As expected, due to the permanent data acquisition, the sentinel node had the highest power consumption. However, the power consumption of the monitoring nodes is not significantly different. Their voltage drop in 45 days is 0.3 V. Since sensor nodes operate correctly for a battery voltage greater than 1.9 V, the expected life-time of the monitoring nodes is 100 days and 90 days that of the sentinel nodes. Relay nodes performed very similar to monitoring nodes.

Figure 9 shows also the time history of battery voltage of the software triggered event detection method described in (Feltrin, Popovic et al. 2016). In this method, the strain sensing hardware described in section 2.1 is operated permanently and event detection is performed based on strain data by embedded data processing. Its operation life-time is approximately 3 weeks. Event driven monitoring with sentinel nodes enables a life-time extension by a factor 5.

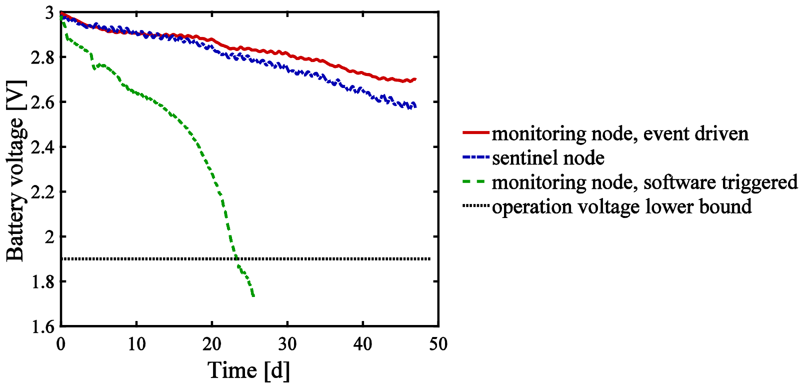

Figure 9: Time evolution of battery voltage of monitoring and sentinel nodes.

4 CONCLUSIONS

This paper presents a wireless monitoring system for strain cycles monitoring on railway bridges. It implements tools such as low power strain sensing hardware, embedded data processing, and event driven monitoring with sentinel nodes. The event driven monitoring system was tested with a field deployment that lasted for 47 days. The test demonstrated that train detection as well as alarming performed very reliably. In only 1.3% of the 3728 detected events not all monitoring nodes received the alarm message. Only 0.3% of the events were missed by all monitoring nodes. This is a small failure rate for this very first field test. Alarm message delivery turned out to be sufficiently fast so that data loss due to late arrival of alarm messages did not occur. The expected life-time of monitoring nodes for the specific deployment is 100 days. For many railway bridges such a monitoring period would already provide a very good data base for a reliable fatigue life assessment.

Nevertheless, there is still space for improvements. The operation life-time of the monitoring nodes can be extended by using 700 Ω in place of 120 Ω strain gages. In addition, the output of data processing can be reduced by selecting a filter threshold that cancels the many small amplitude cycles due to post-event vibrations. On steel bridges, defining a strain cycle amplitude threshold that is smaller than the cut-off limit of the S-N curve of the design details, does not have any effect on the results of fatigue assessment.

The average loss of strain data during the field test was 4.7%. In contrast, the average data loss of battery voltage and network performance data was much smaller, namely 0.5%. The reason for this difference is that the communication of strain data occurred in bursts because of the event driven monitoring policy. Such a burst may temporarily exceed the data throughput capacity of network nodes. Since the network communication protocol used in the test does not guarantee a 100% safe data packets delivery, a small part of data packets went lost. The observed data loss rate due to transmission bursts is not dramatic but still problematic and needs to be reduced.

Although there is still space for improvements, this investigation demonstrates that a suitably designed wireless sensor network is well suited for performing efficiently and reliably strain cycles monitoring on metallic railway bridges.

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