Institute of Operating Systems
and Computer Networks

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Dynamic Sample Rate Adaptation for Long-Term IoT Sensing Applications

WF-IoT 2016

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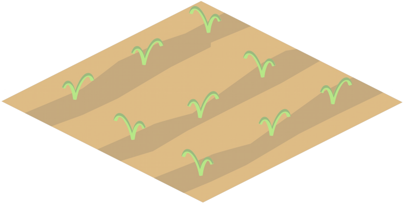
Motivated by (but not limited to) specific application

Smart farming applications

- Usage of WSNs for *precise* and *distributed* sensing



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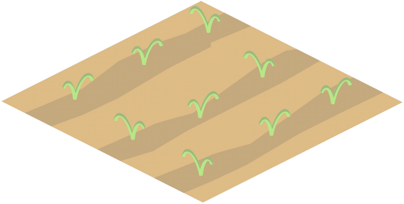
- Usage of WSNs for *precise* and *distributed* sensing
- Monitoring of crops is of major importance
  - Enhance the harvest
  - Optimization of sprinkling, utilization of fertilizers
  - Inevitable with regard to global warming



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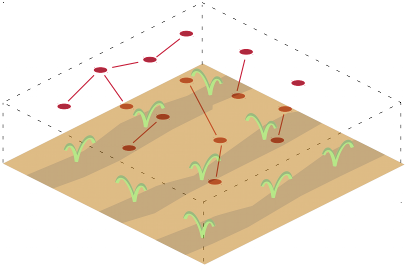

→ Nodes are deployed in rural areas and require long lifetimes

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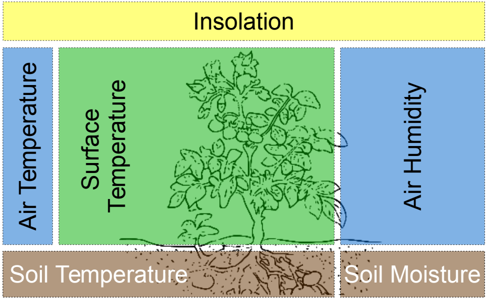
Exemplary: Distributed measurement of the crop water stress index



- Measurement of the *stress* of potato plants
  - Absence of water, inferior soil, …
- Several parameters indicate the condition of crops
  - In particular the surface temperature
- Nodes have to rely on local energy sources
  - Batteries, energy harvesters

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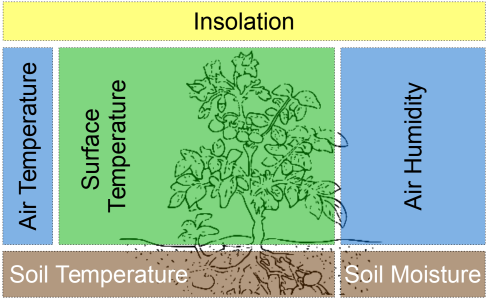

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→ **Data quality** and **energy efficiency** are major requirements

Dynamic sample rate adaptation

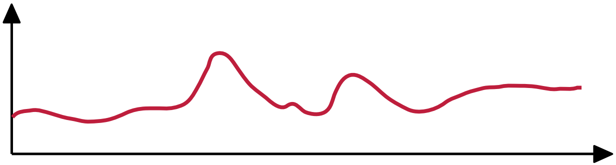
Idea: Decrease the duty cycle of sensors

- General energy consumption of a sensor

$$E_s = T_{s_{active}} \cdot P_{s_{active}} + T_{s_{sleep}} \cdot P_{s_{sleep}} \quad \text{with} \quad P_{active} \gg P_{sleep}$$

- **Adequate** reduction of $T_{s_{active}}$ reduces the energy consumption significantly

Sensor data are a priori unknown



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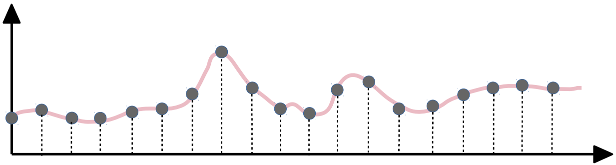
High sample rate



Good data quality but poor energy efficiency

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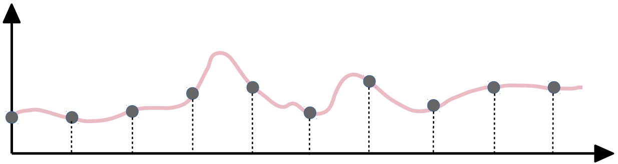
Low sample rate



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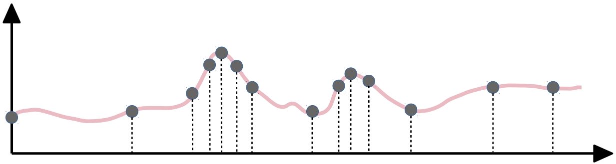
Solution: Dynamic sample rate



Adaptation based on the data $\rightarrow$ Data quality and energy efficiency

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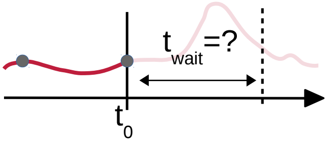
Challenges and general approach

Goal

- Online estimation of the waiting time t_{wait} to the next sample
  - Highly fluctuating data $\rightarrow$ short t_{wait}
  - Steady data $\rightarrow$ longer t_{wait}
- Lightweight solution suitable for WSN nodes



Basic Idea

Utilization of Bollinger Bands

- Introduced in the 1980s by John Bollinger
- Originally a tool to analyze the trend of stock prices

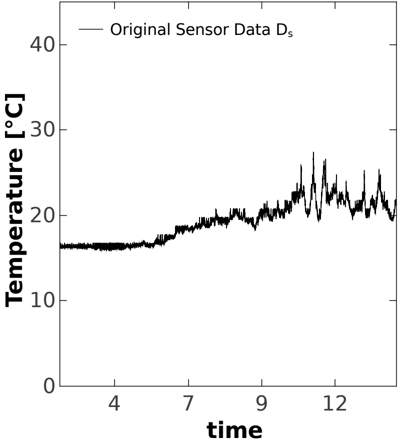
→ Transferring the concept of Bollinger Bands to a series of sampled data

Bollinger Bands – Considering data-points instead of stock prices

Calculation of a Bollinger Band at the time t

- Mid-band $bb_{mid_s}(t)$
  - Moving average of n previous data-points D_s of sensor s

$$bb_{mid_s}(t) = \frac{1}{n} \cdot \sum_{i=0}^{n-1} D_s(t-i)$$



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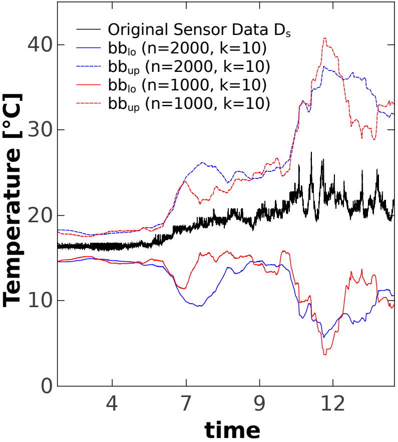
- Upper- and lower-bands $bb_{up_s}(t)$, $bb_{lo_s}(t)$
  - Standard deviation $\sigma_n(t)$ of the n previous data-points $\pm$ mid-band

$$bb_{up_s}(t) = bb_{mid_s}(t) + k \cdot \sigma_n(t)$$

$$bb_{lo_s}(t) = bb_{mid_s}(t) - k \cdot \sigma_n(t)$$



Waiting time estimation

Estimate the next point in time (t_{wait}) to sample new data:

$$t_{wait}(t) = \frac{t_{max}}{1 + dyn(t)^{\varphi}}$$

- t_{max} maximum waiting period
- $dyn(t)$ dynamic estimation function
- φ weighting factor (exponent)

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- φ weighting factor (exponent)

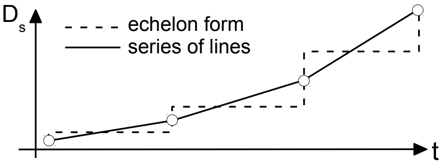
$\rightarrow$ Use width of the Bollinger Bands for dynamic estimation function

$$\Delta_{bb}(t) = |bb_{up_s}(t) - bb_{lo_s}(t)| = \underbrace{2k}_{b} \cdot \sigma_n(t) \quad \rightarrow \quad dyn_{bb}(t) = b \cdot \sigma_n(t)$$

Dynamic estimation function using vertical distances

Width of Bollinger Bands offer a sufficient metric, but is not ideal

- Standard deviation $\sigma_n(t)$ is based on the arithmetic mean
- However, sensor data are represented by lines between samples



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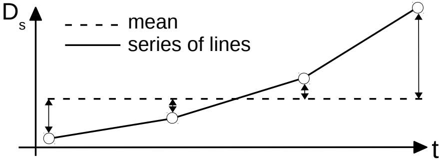
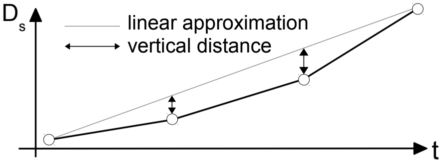


- Assumption: moderate rising/falling trend of data (without fluctuation)

$\rightarrow$ Dynamic estiation function dyn_{bb} increases and energy is wasted

Dynamic estimation function using vertical distances

Optimize dynamic estimation function by using vertical distances



- Consider linear characteristic of data
- Metric is based on the vertical distances between historical data and linear approximation

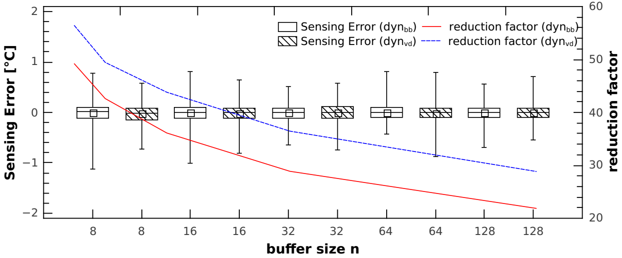
$$dyn_{vd}(t) = \frac{k}{n} \cdot \sum_{i=0}^{n-1} |f(t-i) - D_s(t-i)| \quad \text{with} \quad f(t-i) \text{linear aproximation}$$

Evaluation of the dynamic estimation functions

Reference Data: Temperature measurement of a day (0.3 Hz≙26500 samples)

- Dynamic sample rate adaptation by using
  - Dynamic estimation function using Bollinger Bands dyn_{bb}
  - Dynamic estimation function using vertical distances dyn_{vd}

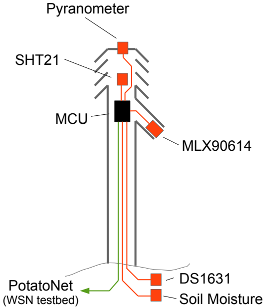
maximum waiting time $t_{max} = 300\,\text{s}$



Real world measurement of the crop water stress index

Deployment of sensor stations on a potato field

- Cooperation with a potato crop research station
- 38 days of measurement
- High sample rate of about 0.3 Hz
  - Collection of reference data



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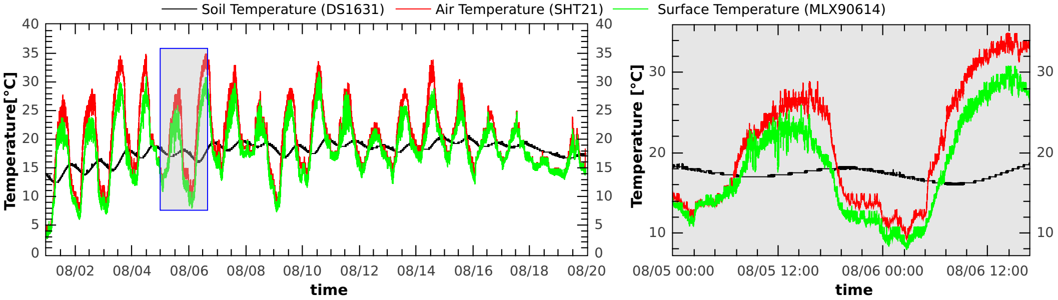
Exemplary data pattern of soil,air and surface temperature



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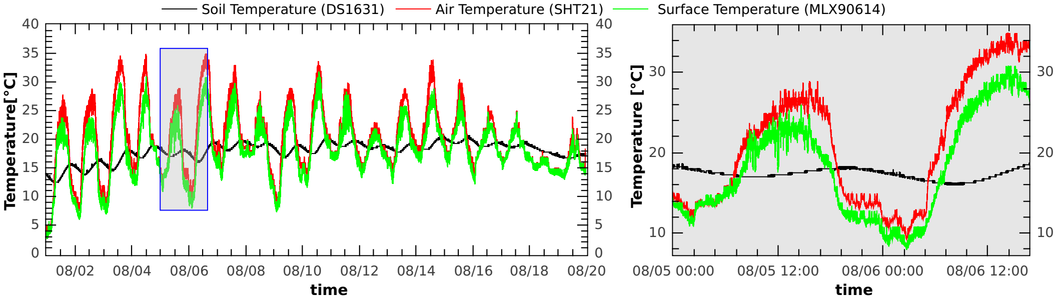

→ Different characteristics of data

Results

Efficiency of dynamic sample rate adaptation (vertical distances)

- Postprocessing of reference data to evaluate the effectiveness for real applications

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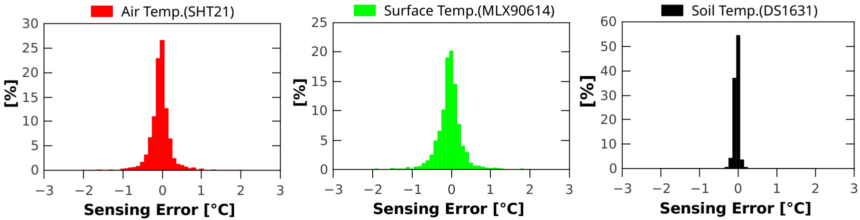
Overall sampling error



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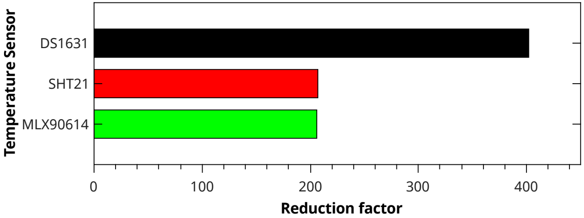
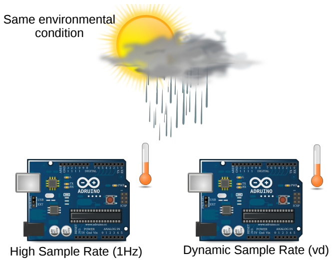
Overall reduction of samplings



Practical test on a low-power MCU

Lightweight implementation of the approach

- Temperature measurement with 2 low-power MCUs
  - 8-bit ATmega328P MCU
- Temperature measurement of a-priori unknown data pattern



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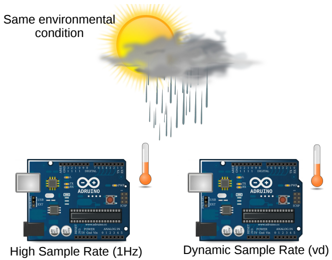

Results compared to the reference node (high sample rate)

- Benefit of the dynamic sample rate adaptation
  1. Works online and sufficiently lightweight
  2. Reduces the energy consumption by 99 %
  3. Sensing error $< \pm 0.5\,\%$ for 91.3 % of data

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Thank you for your attention! Questions?

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