Master thesis defense

Design of an ultra-low-power energy-harvesting audio sensor for ecosystem monitoring

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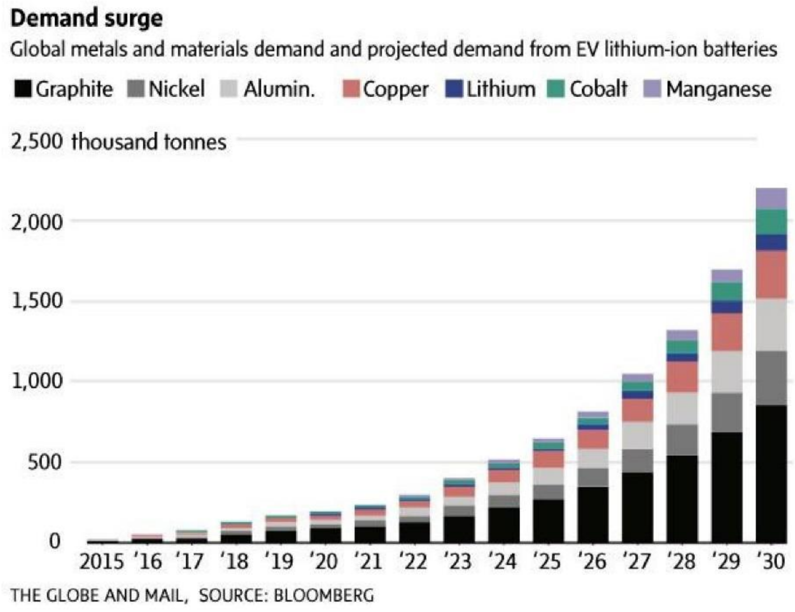
ÉCOLE POLYTECHNIQUE DE LOUVAIN

Context and motivation

Internet of Things (IoT): billions of connected smart sensors

→ Currently **not environmentally sustainable**

- Beforehand: pressure on **critical elements**



- Afterwards: ecotoxicity of **e-waste** (exported, incinerated, landfills)

Context and motivation

Ecosystem destruction: climate change → ecosystem monitoring

- Focus on **monitoring in forest**
    - water and soil conservation [1]
    - genetic resources for plants and animals
    - source of wood supply
    - benefits on human physical and mental health [2]

Current approach: **manual** and sporadic sampling requiring **human presence**

→ evolution characterization limited by low observation frequency

Contribution of this work

Autonomous and efficient **audio smart sensor for bird monitoring**

Use case

- Energy harvesting from environment
- Environmentally-friendly and non-toxic components
- Audio signal processing for bird classification
- LPWAN communication
  - Data transmission
  - Reconfiguation for firmware updates

Outline

- Challenges and requirements
- Design
  - Energy storage
  - Sensing
  - Power management
  - Solar cells and supercapacitor
- Validation
  - Model view
  - Power budget and MPPT
- Inference for bird monitoring
  - Algorithm
  - Live demo
- Conclusion and outlook

Design: energy storage

	Capacitors			Batteries		
	Ceramic	Electrolytic	Supercap EDLC	Non-rechargeable Alkaline	Rechargeable NiMH	Rechargeable Lithium ion
Power density [W/g]		> 100	2 – 10		2.5 – 10	1 – 3
Energy density [mWh/g]	0.1 [21]	0.01 – 0.3	5		60 – 120	120 – 240
Self-discharge rate [per month]	100%	100 h	50%	< 0.3%	0.08 – 2.9%	5%
Leakage current	1 – 100 nA/µF		2 – 5 fA/µF [22] [23]			5 µA [21]
Service life [years]	25 [21]	15	10 – 15	5 – 10		5 –10
Life cycles	unlimited [21]	unlimited	1 000 000	1	180 – 2000	500
Degradation	negligible		-80% in 10 years			-50% in 500 cycles
Charge time			1 – 10 s			10 – 60 min
Cell voltage [V]		4 – 630	2.3 – 2.75	1.5	1.2	3.6
Charge T° [°C]		-40 – 70	-40 – 65			0 – 45
Discharge T° [°C]		-40 – 70	-40 – 65			-20 – 60
Discharge efficiency		99%	95%		66% – 92%	90%
Toxicity			low			middle

Supercapacitors: good trade-off between

- capacitors: high power density → fast (dis)charge
- rechargeable batteries: high energy density → reduced volume

High service life

But high leakage current

Design: energy storage

Critical and toxic elements overused in electronics: lithium, cobalt, gold, silver, ...

	Li-ion batteries	Supercapacitors
Electrodes	lithium, nickel, cobalt, graphite	porous carbon (graphite)
Electrolyte	lithium salts	liquid salts (lithium)

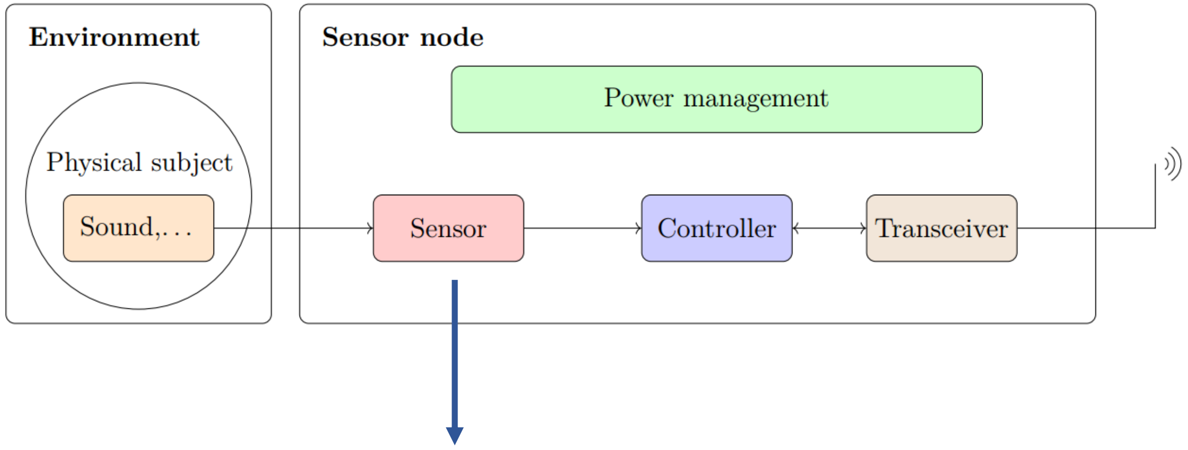
→ Selection for this work: **supercapacitors** (far less toxic and resourse-intensive)

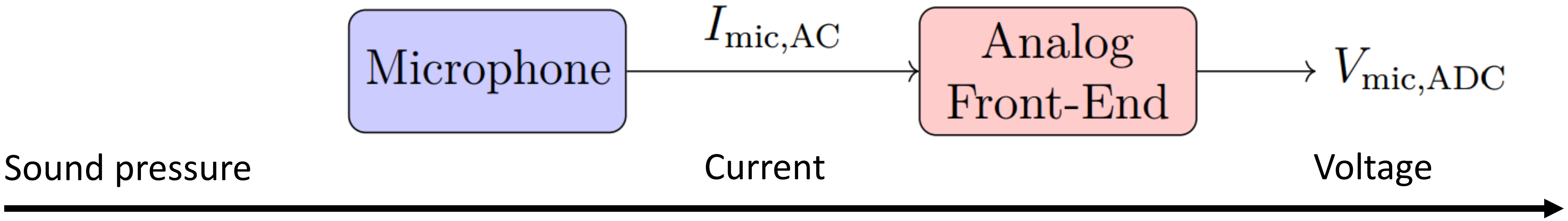
Design: sensing

Physical stimulus: **sound wave** (in dB or dBSPL)

- Transduced with a microphone
- 50m detection
- Bird frequency range (1kHz - 8kHz)

Pressure range	16 – 61	$\mathrm{dB_{SPL}}$
Frequency range	20 – 20000	Hz





Design: sensing

IoT applications: **condenser microphones** (MEMS or **electret**)

- Figures of merit

Power consumption

Self-noise

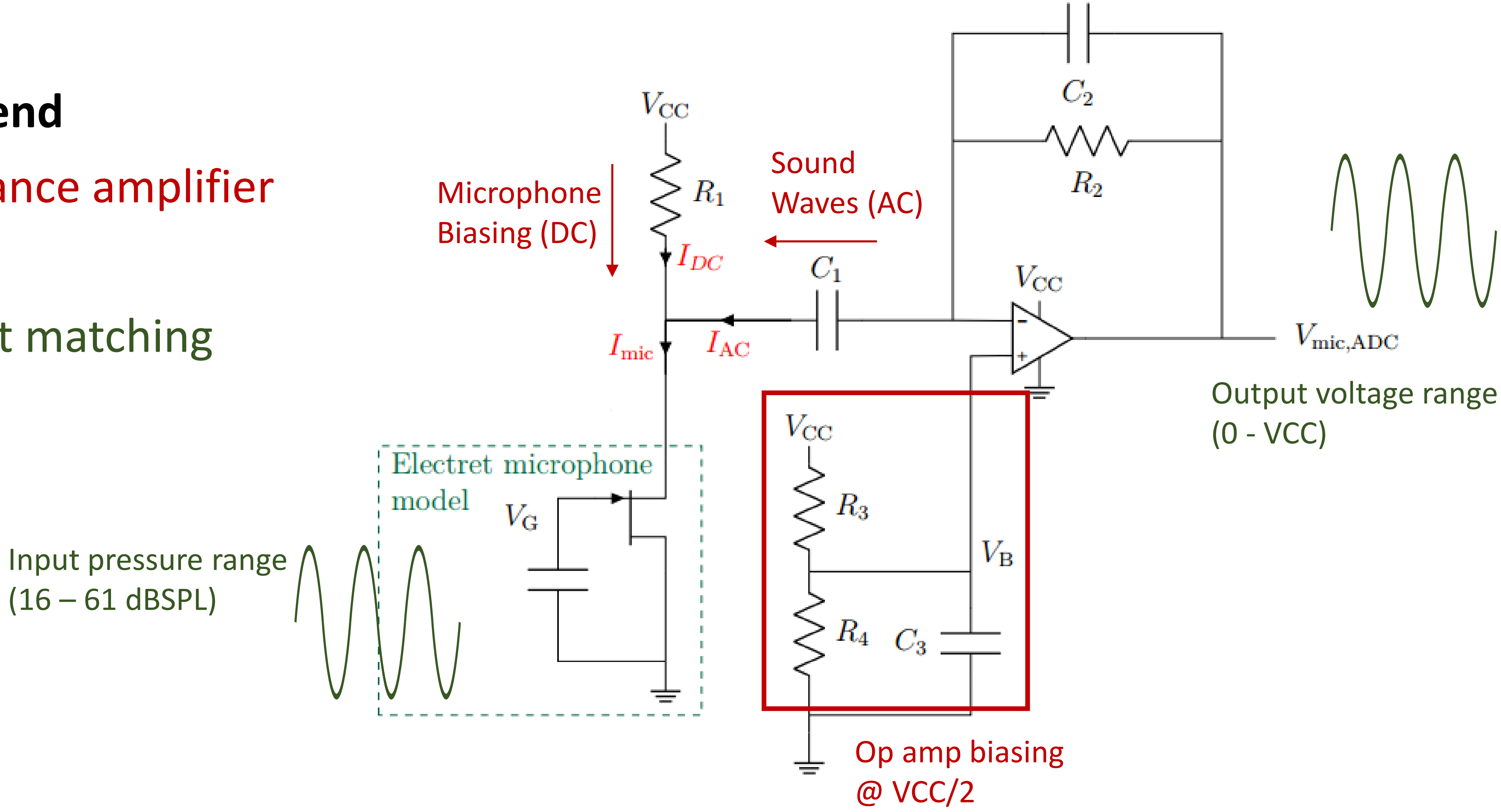
	ABM-707-RC	CMC-6027-24L100	AOM-5024L-HD-R
Current [µA]	500	500	$\boxed{500}$
Voltage [V]	1.5	2	$\boxed{2}$
Sensitivity [dB]	-41	-24	-24
SNR [dB]	60	70	$\boxed{80}$
Output impedance [Ω]	2.2	2.2	2.2
Frequency range [Hz]	50 – 16000	100 – 20000	20 – 20000
Temperature [°C]	-20 – 60	-20 – 70	-30 – 70

Very **low noise** (with same power consumption)

Design: sensing

Analog front-end

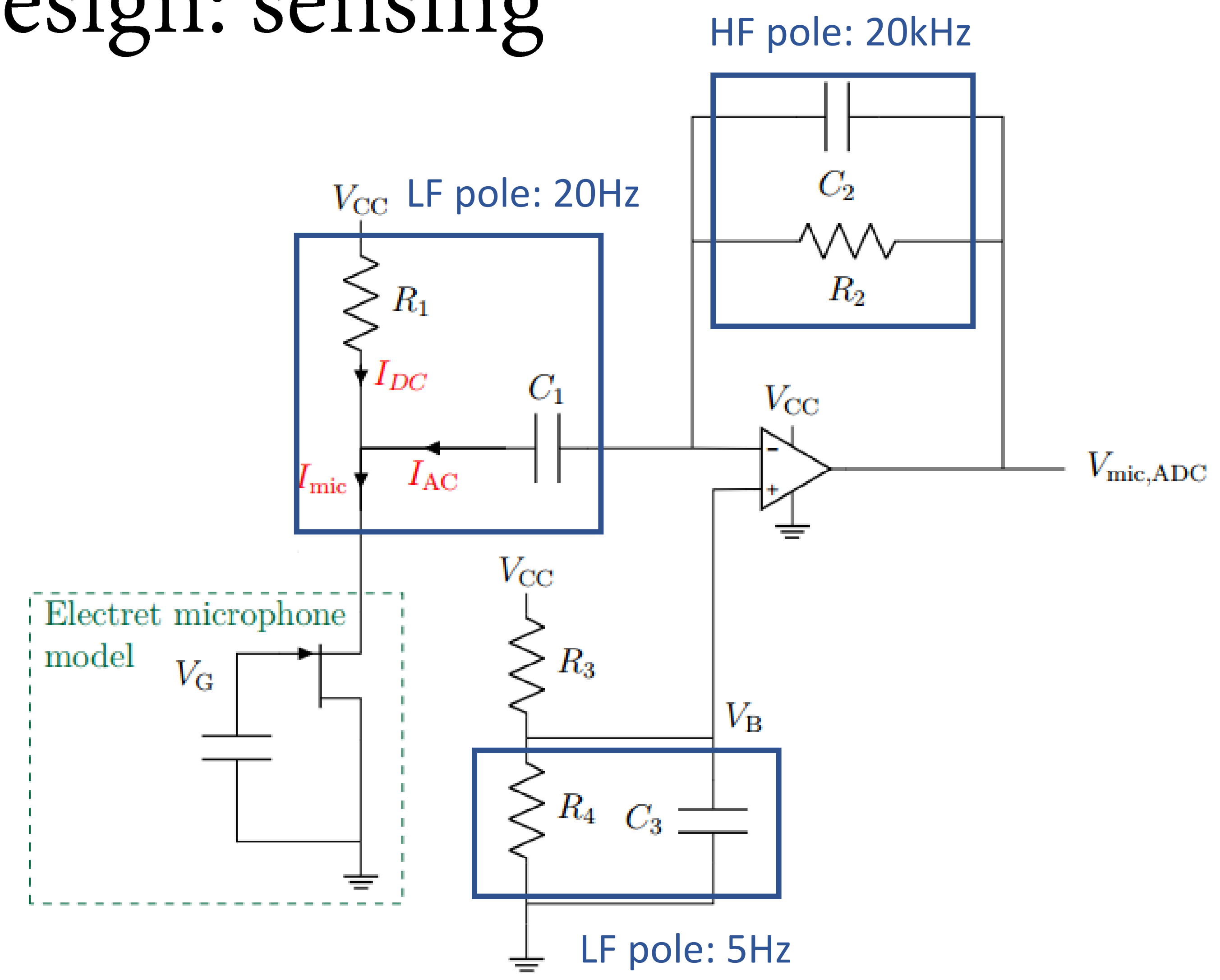
- Transimpedance amplifier
- Input/output matching



Design: sensing

Analog front-end

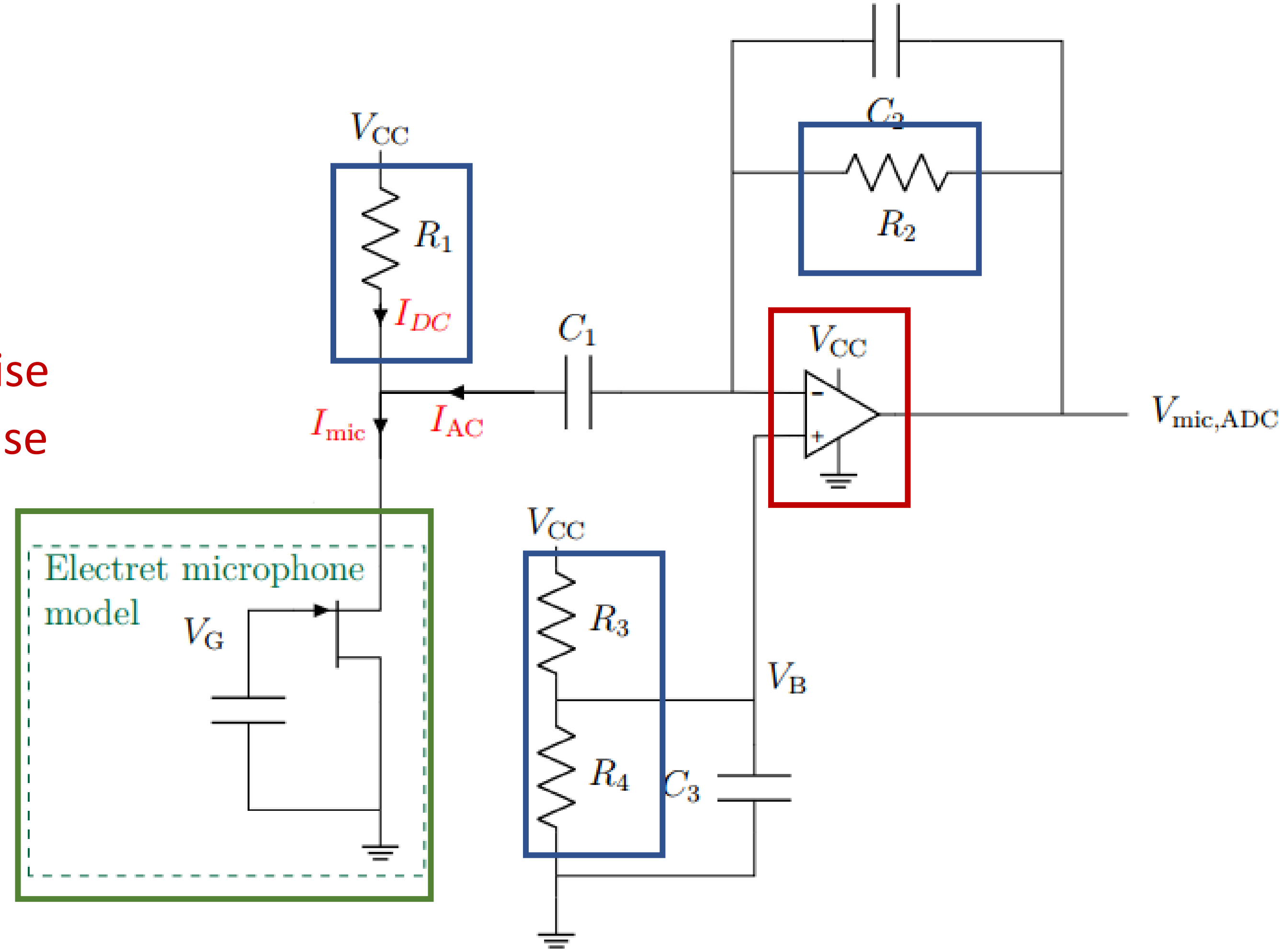
- Transimpedance amplifier
- Input/output matching
- Pole placement



Design: sensing

Analog front-end

- Noise
  - Thermal noise (resistors)
  - Op amp input-refered current noise
  - Op amp input-refered voltage noise
  - Microphone self-noise



Design: sensing

Analog front-end

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  - Op amp input voltage noise
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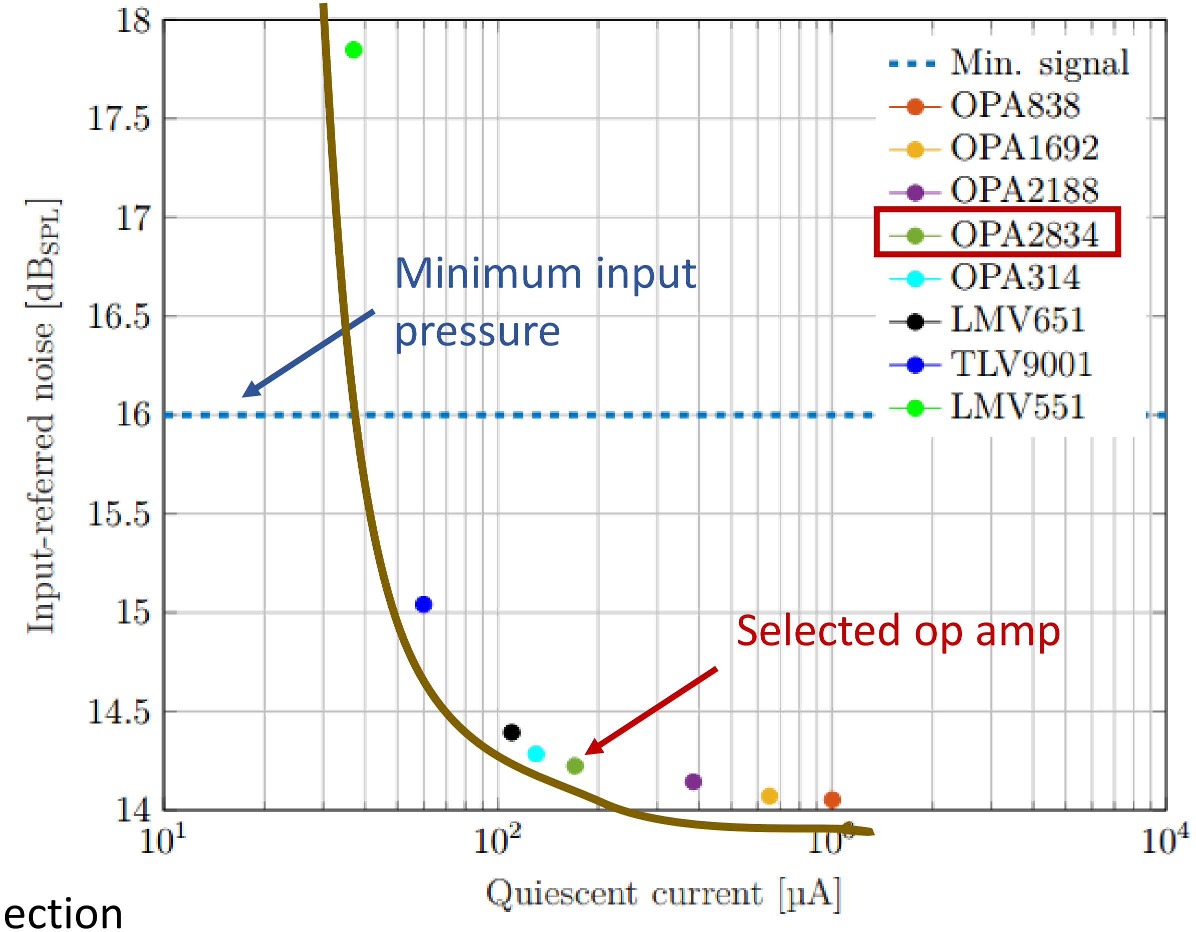
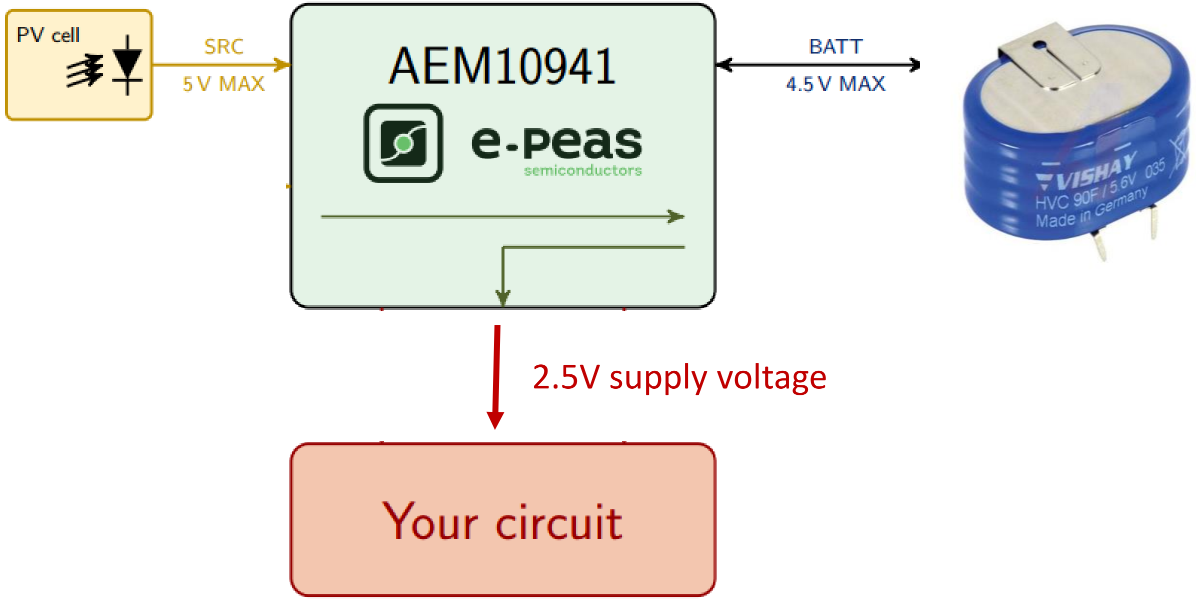


Pareto front

→ **trade-off *noise/power consumption*** for op amp selection

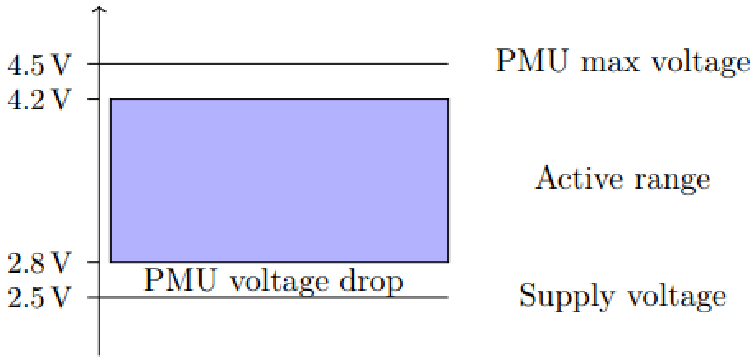
Design: power management

Power management unit from *e-peas*



- Energy
    - **Harvesting**: solar cells (with MPPT)
    - **Storage**: supercapacitor

- Low-dropout (LDO) regulation
    - with low quiescent current



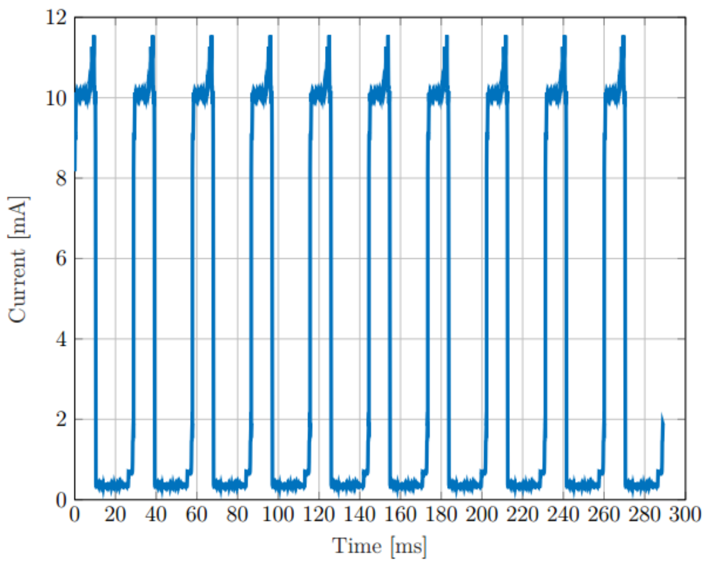
Design: power consumption

Current budget

(Power budget $P_{batt} = V_{batt} I_{tot}$ depends on supercap voltage since LDO in PMU)

- Sensing
  - Microphone biasing
  - Op-amp supply
- Power management
  - Supercap leakage
  - PMU quiescent current
- Data processing (MCU/RF)
  - Alternance run / sleep modes with limited duty cycle (1/3)

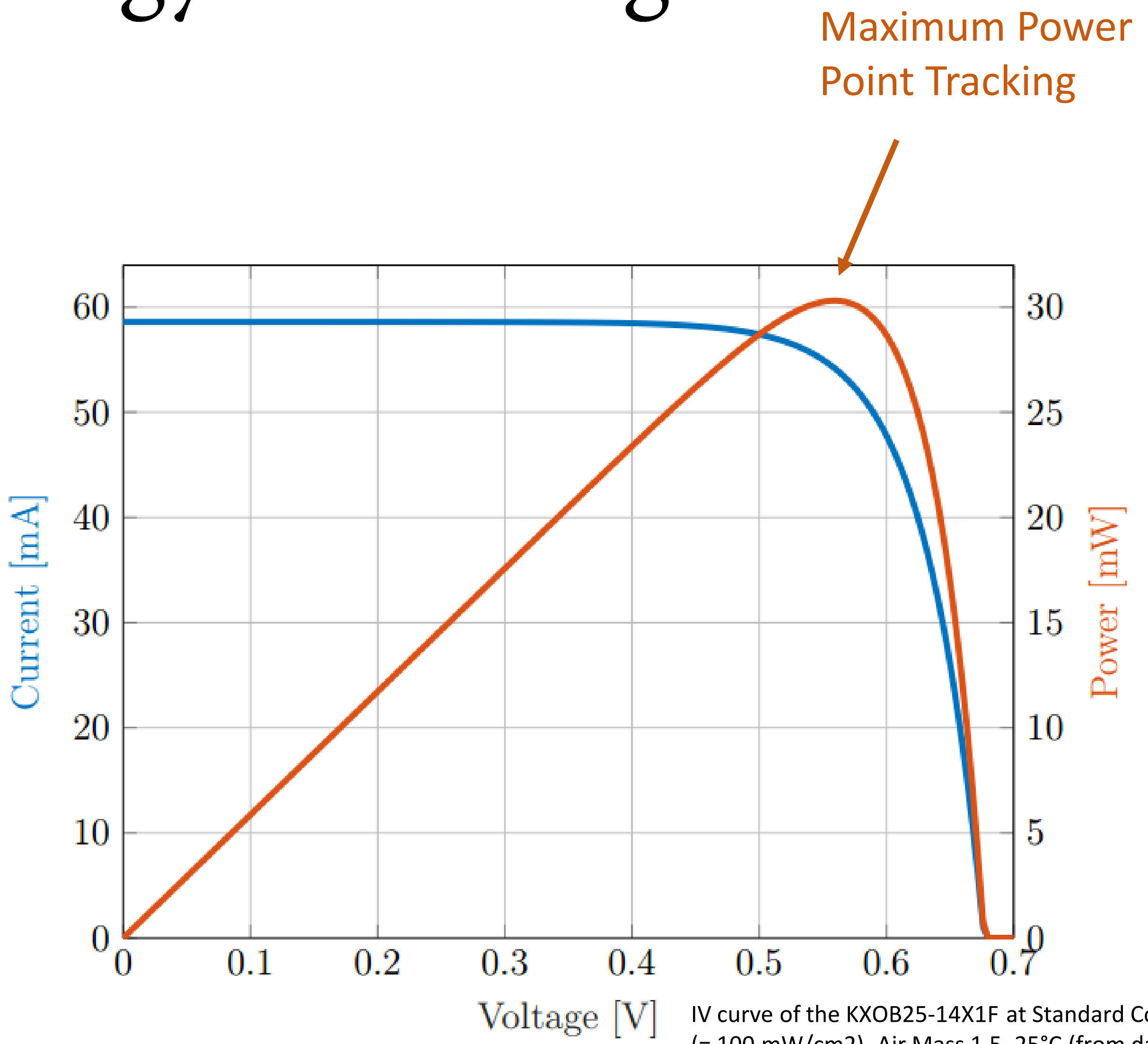
	Current [mA]
Data processing	3.88
Power management	0.50
Sensing	0.54
Total	4.92



Design: energy harvesting

Solar cells

- Voltage adaptation for maximum power harvesting
- Maximization of harvested power per unit area

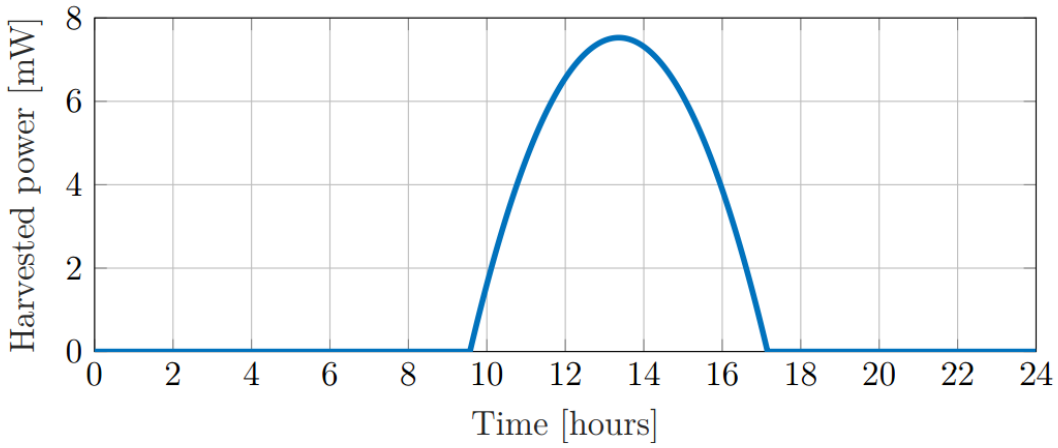


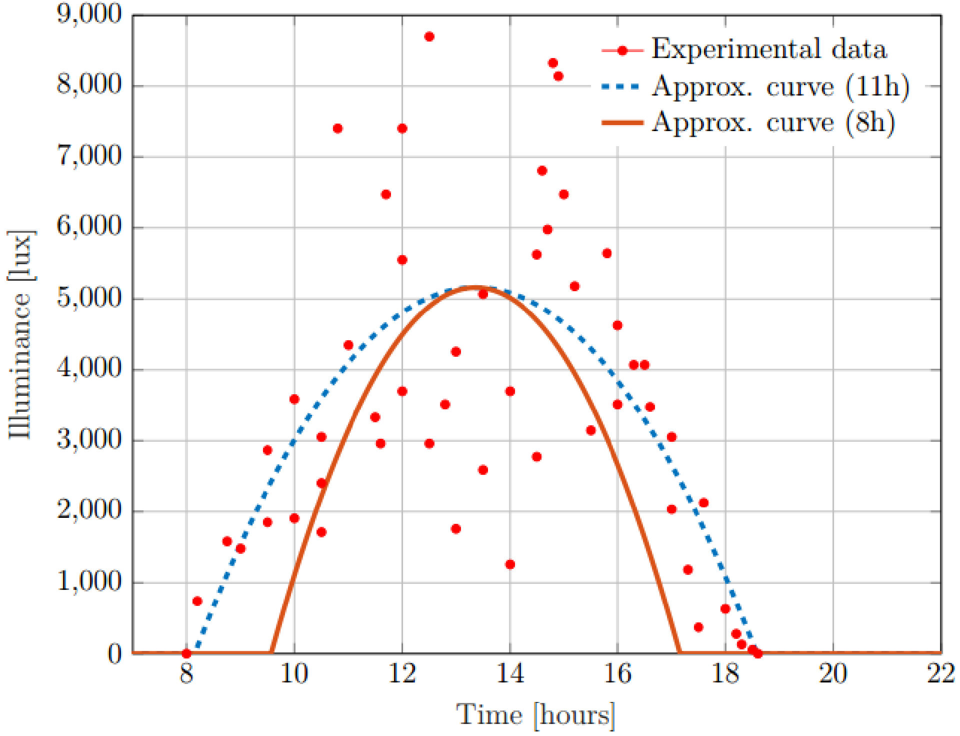
IV curve of the KXOB25-14X1F at Standard Condition: 1 sun (= 100 mW/cm2), Air Mass 1.5, 25°C (from datasheet)

Design: energy harvesting

Solar cells

- Luminosity profile along the day
  - → Estimation of harvested power





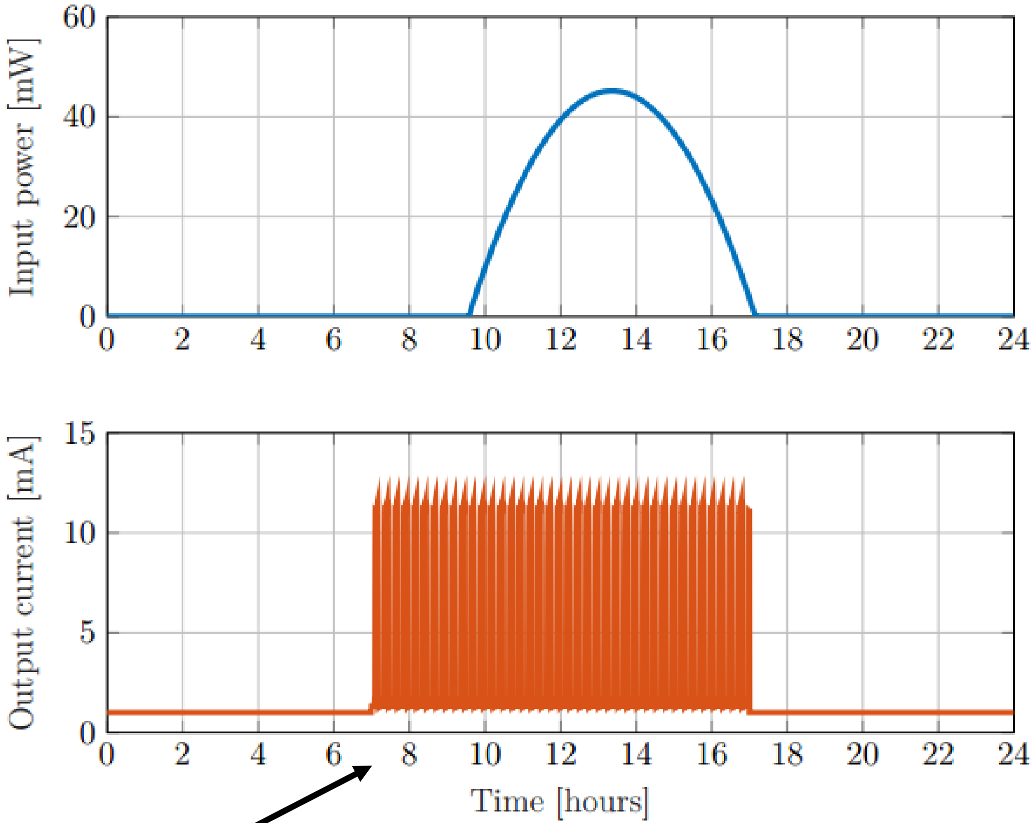
Daily luminosity In a shady place
(Louvain-la-Neuve, from March 3 to March 6, 2020)

Design: energy harvesting

Summary

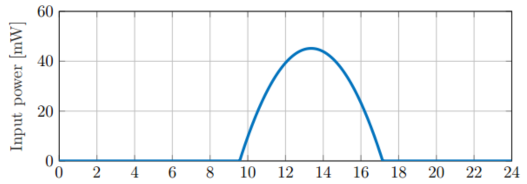
Input power
(1 cell)

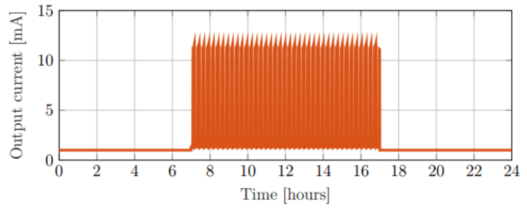
Output current

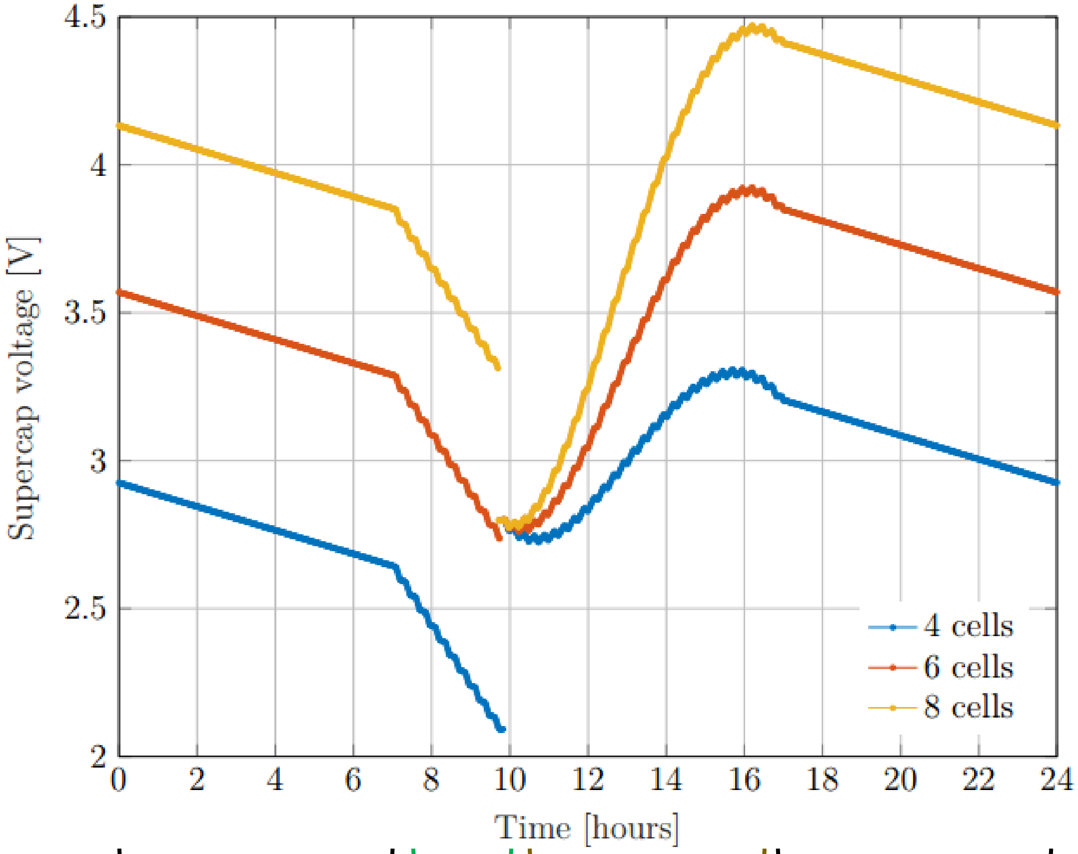


MCU in operation only during the day (for power reduction)

Design: solar cells



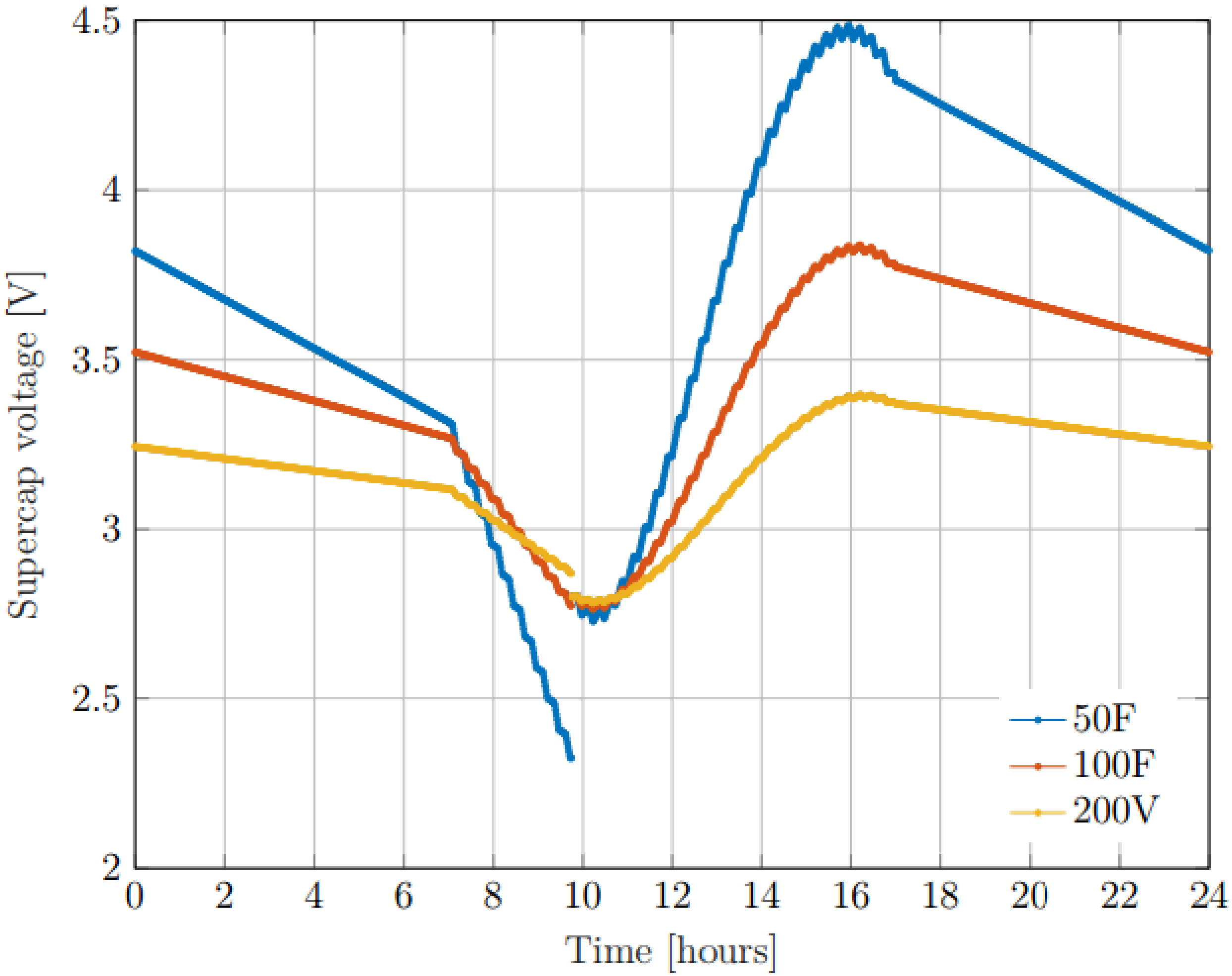


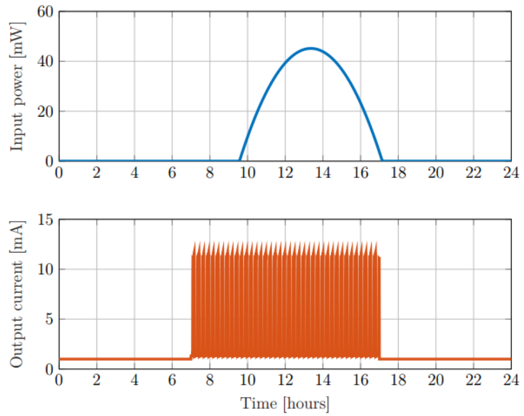


→ **6 solar cells** required

~~MCU~~ ~~Sun~~	MCU ~~Sun~~	MCU Sun	~~MCU~~ ~~Sun~~

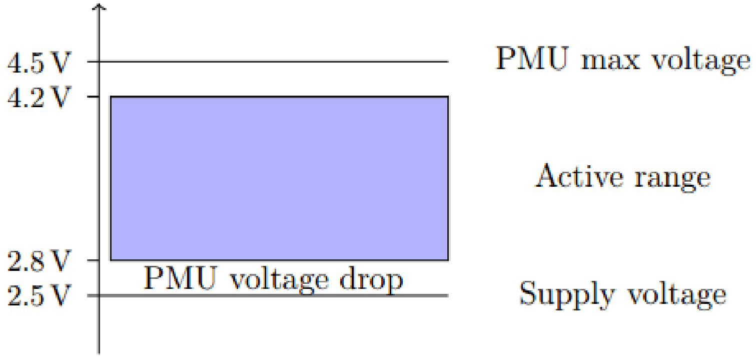
Design: supercapacitor





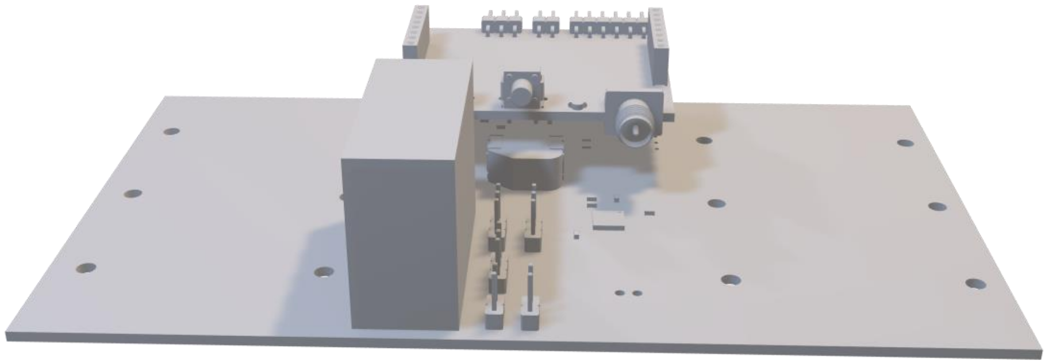
90F/4.2V supercapacitor required

- Below the 4.5V PMU limit
- Avoids high voltage → keep high LDO efficiency



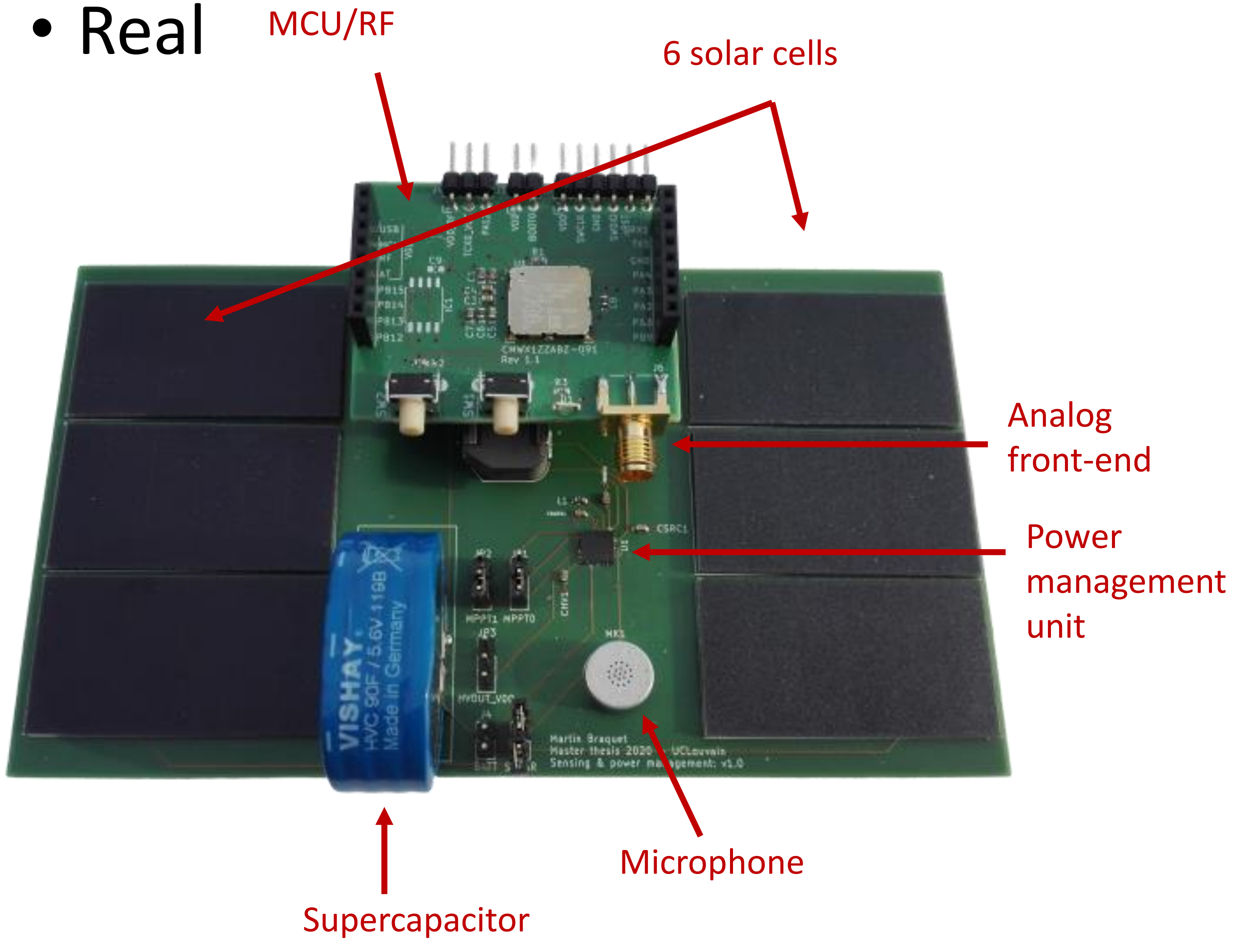
Validation: model view

- CAD



Dimensions: 143 mm × 82 mm × 25 mm

- Real



Validation

- **Power budget**

	Experimental current	Theoretical current
Supercap leakage	90 µA	500 µA
Sensing	904 µA	536 µA
Power management unit	0.5 µA	0.6 µA
Microcontroller	3.88 mA*	(measured experimentally)
Total	**4.874 mA**	**4.916 mA**

*MCU current consumption (run/sleep duty cycle of 1/3) for
- ADC sampling @ 20kHz
- FFT operations (N = 128)
- Bird inference

- **Maximum power point tracking**

MPPT ratio	Voltage [V]	Current [mA]	Power [mW]
70%	2.9	20.2	58.6
75%	3.11	17.9	55.7
85%	3.53	11.1	39.1
90%	3.73	3.5	13.1

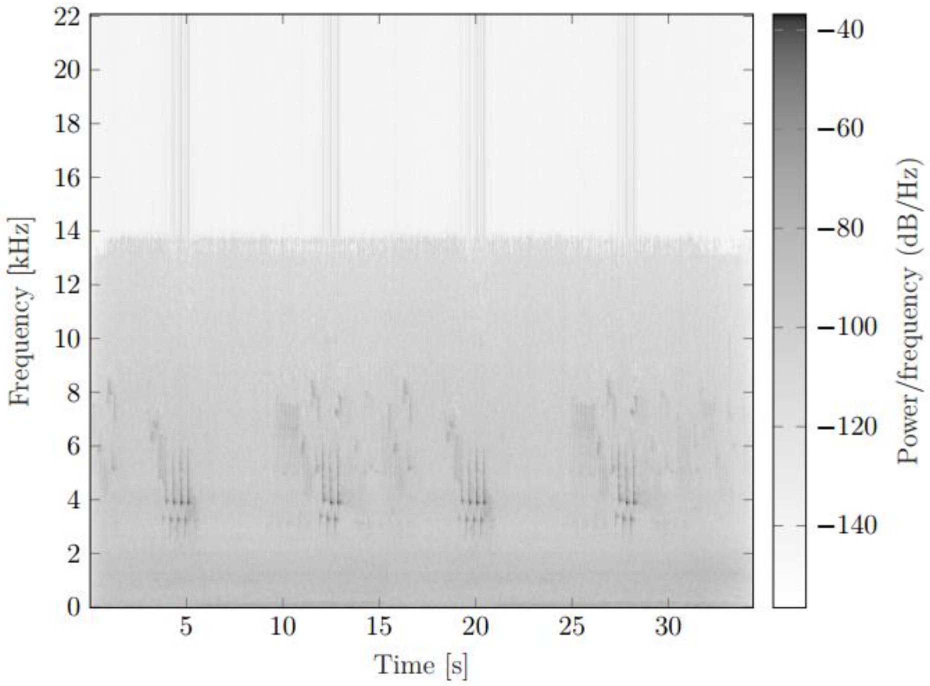
Inference algorithm

Bird species discrimination inside the microcontroller

- Among 4 common species in Europe: pigeon, blackbird, great tit and blue tit
- Limitations: memory, speed (≈ power)
- Fast Fourier transform (FFT): spectral domain
  - Use of spectrogram
- Machine learning approach (KNN)

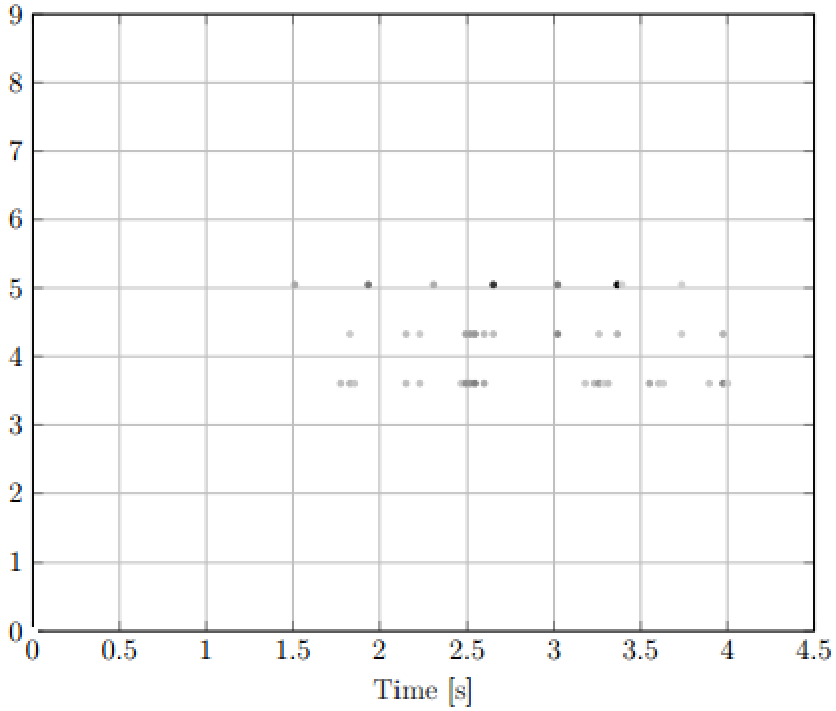
Inference algorithm

Spectrogram: time-frequency representation of audio signals



Post-processed spectrogram

(4 great tit songs at regular intervals)



On-chip spectrogram

(One great tit song)

→ Trade-off **time / frequency resolution**

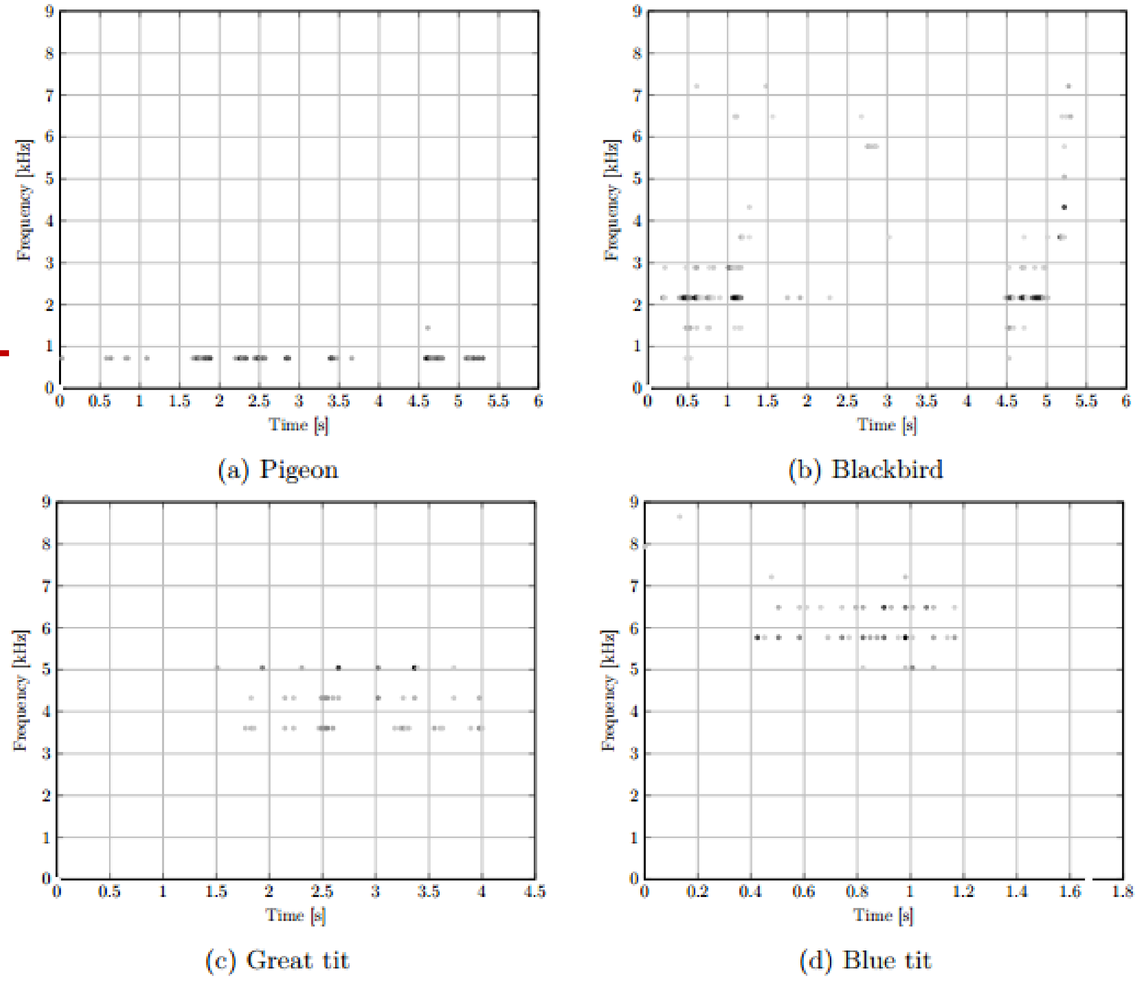
- **FFT size: 128**
- **Sampling frequency: 20 kHz**

↓

Frequency resolution: 156 Hz

Inference algorithm

Different **frequency range** for each bird



(a) Pigeon (b) Blackbird

(c) Great tit (d) Blue tit

≈ 1 kHz

≈ 2 kHz

≈ 4 kHz

≈ 6 kHz

Inference algorithm

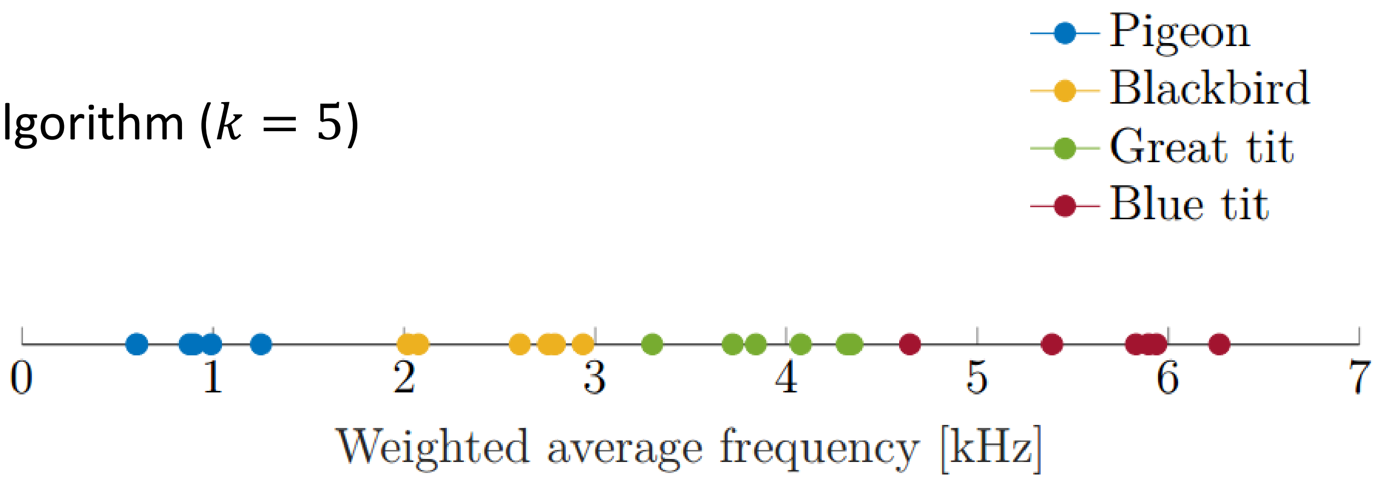
$$f_{\text{avg}} = \frac{\sum_{j=1}^{L} s_{\text{avg}}[i]\, f[i]}{\sum_{j=1}^{L} s_{\text{avg}}[i]} \quad [\text{Hz}]$$

$$s_{\text{avg}}[i] = \frac{1}{M} \sum_{j=1}^{M} s[i,j]$$

Mean amplitude
@ f[I]

Machine learning approach

- Feature extraction: weighted average frequency
  - Mean frequency of the whole spectrogram
- Feature selection
  - Only one feature for reduced complexity
- Inference
  - k-nearest neighbors (KNN) algorithm ($k = 5$)
- Learning phase
  - 6 audio samples per species



Inference algorithm

Machine learning approach

- Validation phase

On learning samples

94% recovered

Species	Number of correct predictions
Pigeon	6/6
Blackbird	6/6
Great tit	6/6
Blue tit	4/6

On new test samples
(3 per species)

All recovered
(but small test set)

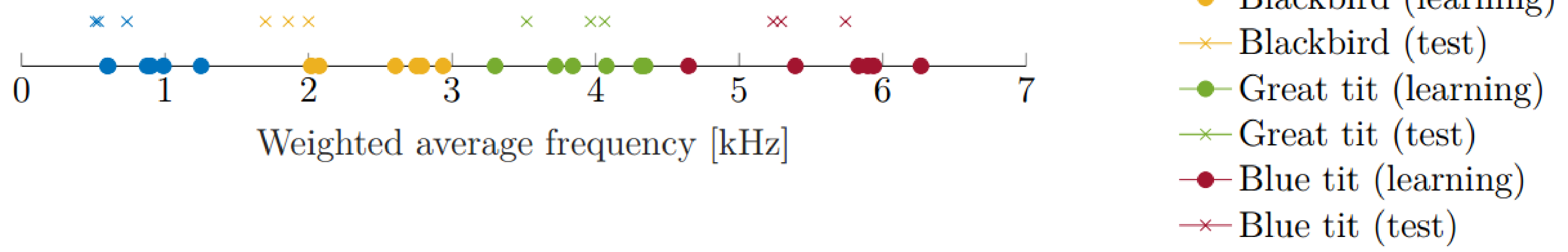


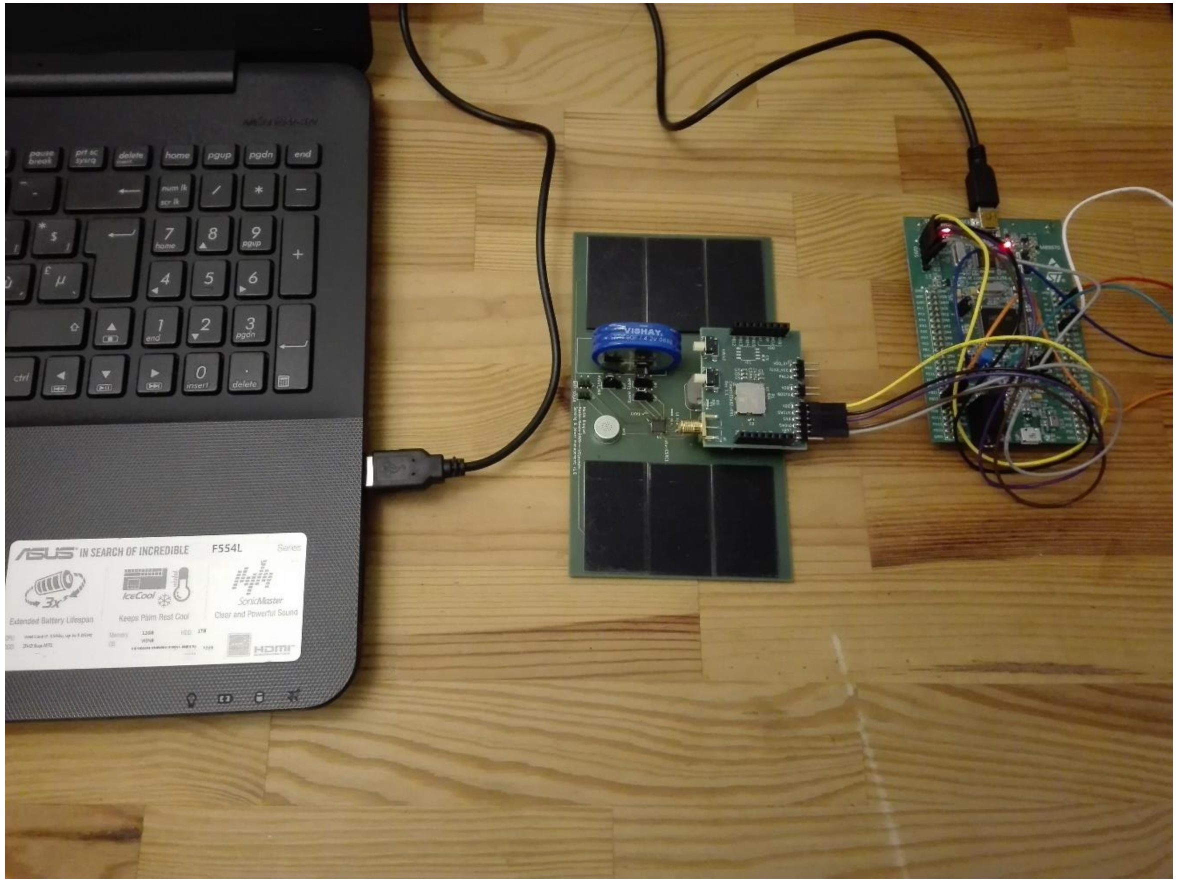
Figure 9.6: Predictions on new samples with the sensor node

Inference algorithm

Live demo

- Bird classification
- Sound generated from laptop speakers

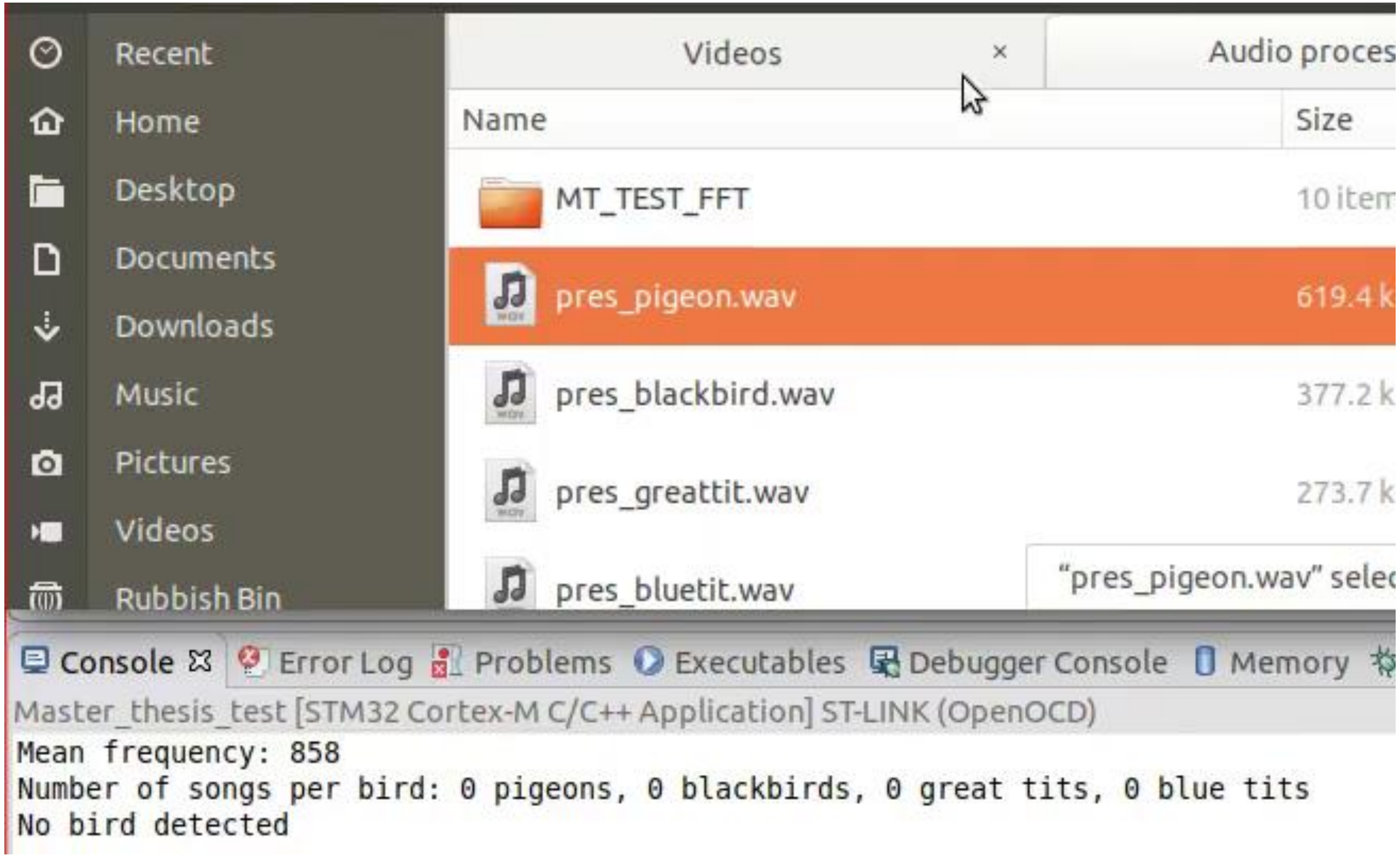
- Pigeon
- Blackbird
- Great tit
- Blue tit



Inference algorithm

Live demo

- Backup video



Conclusion

Ultra-low-power energy-harvesting audio sensor for ecosystem monitoring

- Fully autonomous and sustainable
  - Context of resource saturation in IoT

Electret microphone

- Amplification circuit: trade-off noise / power in op-amp

Solar cells

- MPPT optimization
- Daily luminosity estimation

Supercapacitor

- Less toxic and resource-intensive
- Good trade-off power / energy density

Important demand for forest monitoring

- Context of climate change

Bird classification

- Spectrogram: trade-off time / frequency resolution
- KNN algorithm: simple but fast (low power)

Conclusion

SWOT analysis

	Positive	*Negative*
Internal	**Strengths**: • Fully autonomous and low power • Long lifetime (15+ years) • Environmentally-friendly • Bird classification	**Weaknesses**: • Resource-limited inference algorithm • Size of the sensor node • Production cost
External	**Opportunities**: • High demand for sustainable sensors and forest monitoring • Rising of low-power machine-learning algorithms	**Threats**: • Harsh environmental conditions

Important numbers

- Lifetime: > **15 years**
- Supply voltage: **2.5 V**
- Average power: **20 mW**
- Input referred noise: **14.22 dBSPL**
- Sound pressure range: **16 – 61 dBSPL**
- Sound frequency range: **20 – 20k Hz**
- Detection duty cycle: **1/3** (during the day)
- Classification: **4 birds** (**94%** accuracy)

Comparison with state of the art

Custom integrated circuit for ML inference in **hardware**

Audio smart sensors

	This work	Pham, 2014 [3]	Zhao, 2012 [4]	Badami, 2015 [5]
Power supply	Supercap + solar cells	Rechargeable batteries (AA)	Rechargeable batteries	/
Power consumption	20 mW	330 mW	73 mW	6 µW
Manual recharge	Never	Every night	Every week	/
Sampling rate	20 kHz	8 kHz	8 kHz	2 kHz
CPU frequency	32 MHz	47.5 MHz	48 MHz	640 Hz (feature extraction)
Microphone	Electret	MEMS	Electret	Passive
Use case	Bird monitoring	Audio streaming	Audio surveillance	Voice Activity Detection

Not autonomous

→ Power consumption only suited for batteries

→ Low sampling rate not for HF bird songs

Outlook

❖ Power management

- **Reduce power consumption** → reduced size/cost of the device
- But less precise and frequent audio monitoring
  - Impact analysis of the duty cycle on the inference precision

❖ Refinement of inference algorithms

- Current algorithm
  - Limited to **4 bird species**
  - Bird counter
  - Sounds from other birds, people or traffic (**false positive detections**)
- More **complex ML algorithms**
  - CNNs/RNNs, LSTMs: deep learning for spectrogram analysis
- Optimization of **power/precision trade-offs** in microcontroller

References

[1] Z. Biao, L. Wenhua, X. Gaodi and X. Yu. “Water conservation of forest ecosystem in Beijing and its value”. Ecological Economics, Volume 69, Issue 7, pages 1416-1426, 2010.

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[3] C. Pham, P. Cousin and A. Carer, “Real-time on-demand multi-hop audio streaming with low-resource sensor motes”. *39th Annual IEEE Conference on Local Computer Networks Workshops*, Edmonton, AB, 2014, pp. 539-543, doi: 10.1109/LCNW.2014.6927700.

[4] G. Zhao, M. Huadon, S. Yan and L. Hong. “Design and Implementation of Enhanced Surveillance Platform with Low-Power Wireless Audio Sensor Network.” International Journal of Distributed Sensor Networks, (May 2012). doi:10.1155/2012/854325.

[5] K. M. H. Badami, S. Lauwereins, W. Meert and M. Verhelst. “A 90 nm CMOS, 6μ Power-Proportional Acoustic Sensing Frontend for Voice Activity Detection.” in IEEE Journal of Solid-State Circuits, vol. 51, no. 1, pp. 291-302, Jan. 2016, doi: 10.1109/JSSC.2015.2487276.

Questions and discussion

Challenges and requirements

- Sustainability
  - → lifetime exceeding 15 years
- Low toxicity and scarcity
  - → material selection (energy storage element)
- Limited deployment of wireless sensor nodes (WSNs)
  - → sound detection up to 50 m
- Limited power and data rate of low-power communication protocols
  - → local data storage and processing
- Robust bird discrimination
  - among a small group of common birds

Design: microcontroller and transceiver

- CMWX1ZZABZ chip with
  - **Microcontroller**: STM32L072
    - Ultra-low-power
  - **Transceiver**: SX1276
    - For long-range and low-power communications (LoRa)

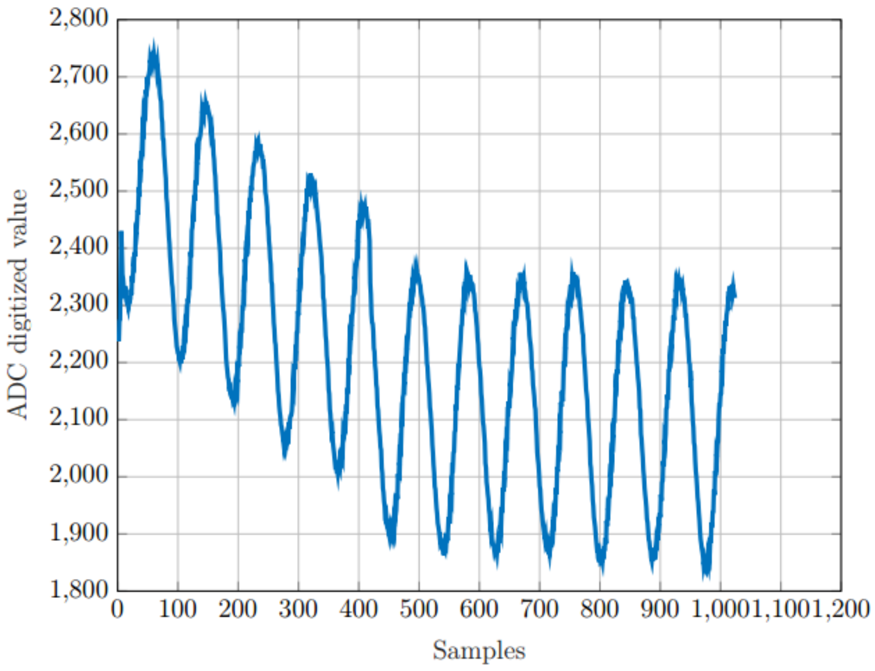
Important characteristics

- Operating voltage: **2.2V – 3.6V**
- 12-bit ADC

Validation

- **1kHz sine wave analysis**

Digitized data



Post-processed FFT