SAPIENZA
UNIVERSITÀ DI ROMA

ENERGY HARVESTING: HOW TO INCREASE THE NETWORK LIFETIME BY RENEWABLE ENERGIES

IOT CLASS 2017/2018

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WIRELESS SENSOR NETWORK (WSN)

ENERGY MANAGEMENT

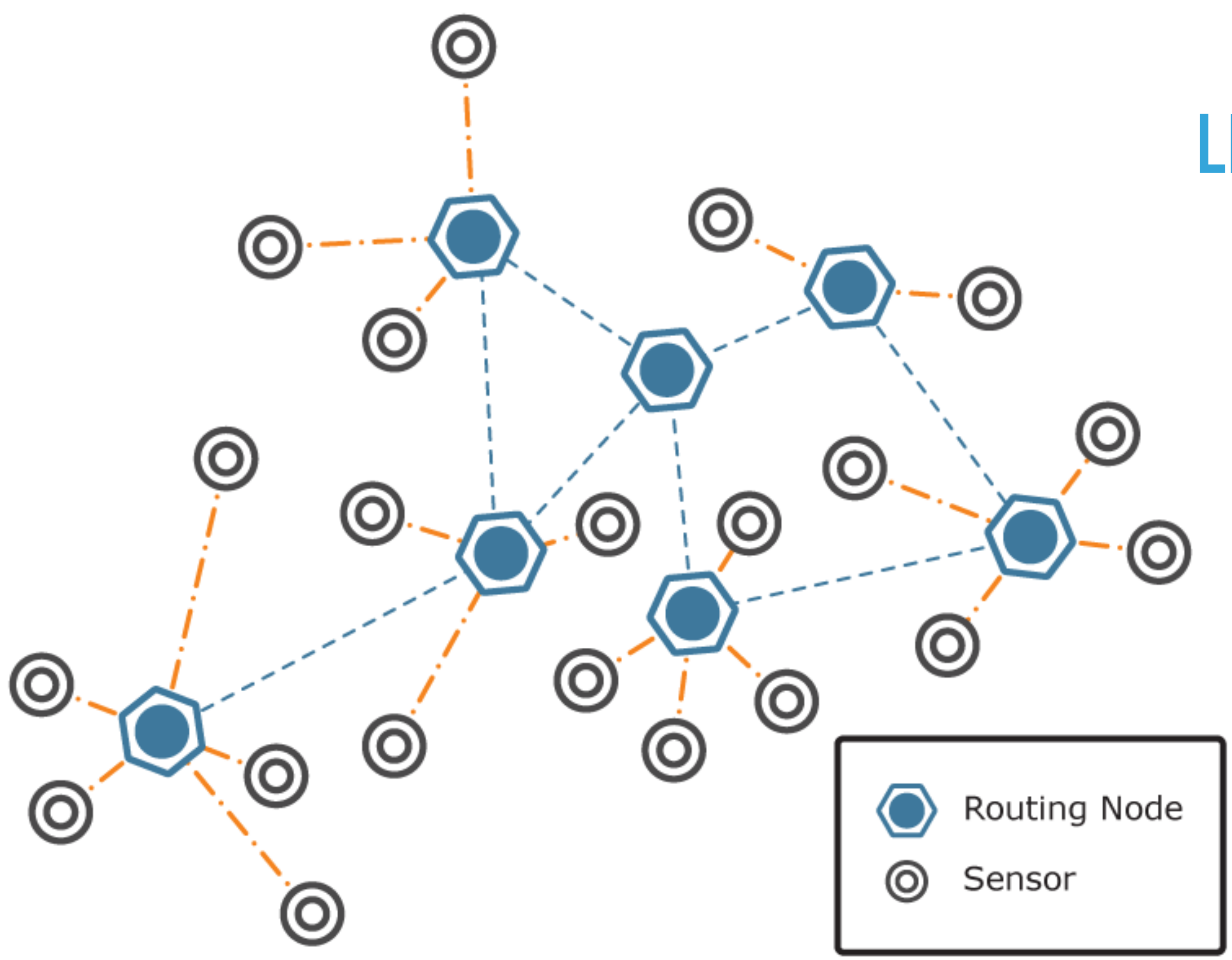
ENERGY HARVESTING

PREDICTION MODELS

ENERGY HARVESTING APPLICATIONS

WIRELESS SENSOR NETWORKS (WSN)

"A WSN is a wireless network consisting of spatially distributed autonomous devices using sensors to **monitor** physical or environmental conditions"



LIMITED COMPUTATIONAL RESOURCES

LIMITED ENERGY RESOURCES

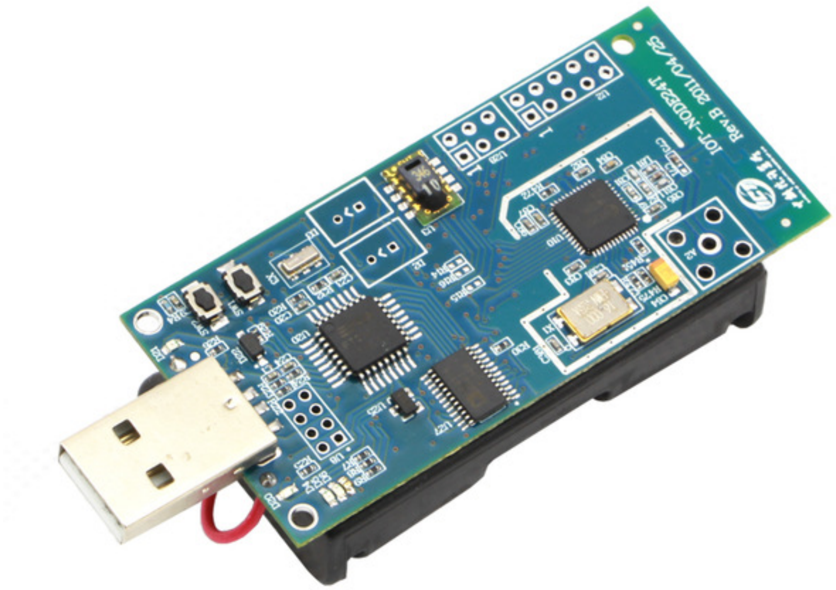
AUTONOMOUS NETWORK

SENSING

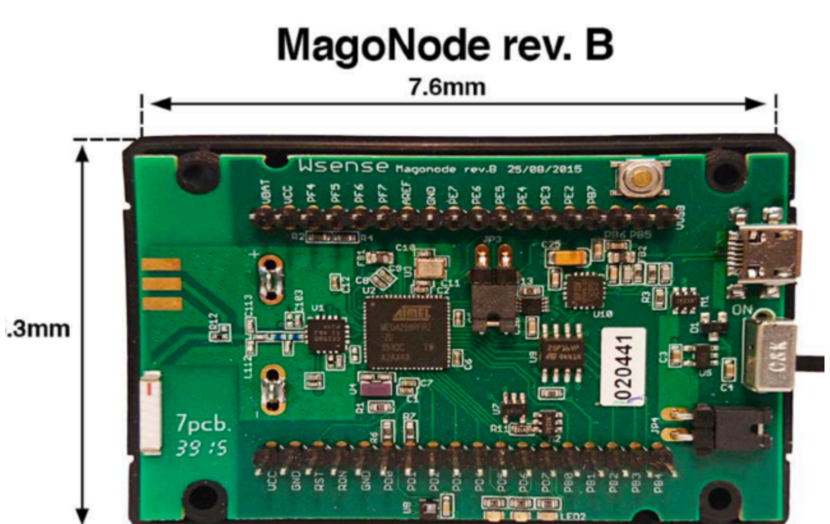
SCALABILITY

MOBILITY

COMPUTATIONAL AND ENERGY RESOURCES



STANDARD
AA BATTERIES



TELOSB

8 MHz TI MSP430 microcontroller with 10kB RAM

1MB external flash for data logging

IEEE 802.15.4 compliant RF transceiver

Sensor suite including integrated light, temperature and humidity sensors

MAGONODEB

16 MHz ATmega256 microcontroller with 32kB RAM

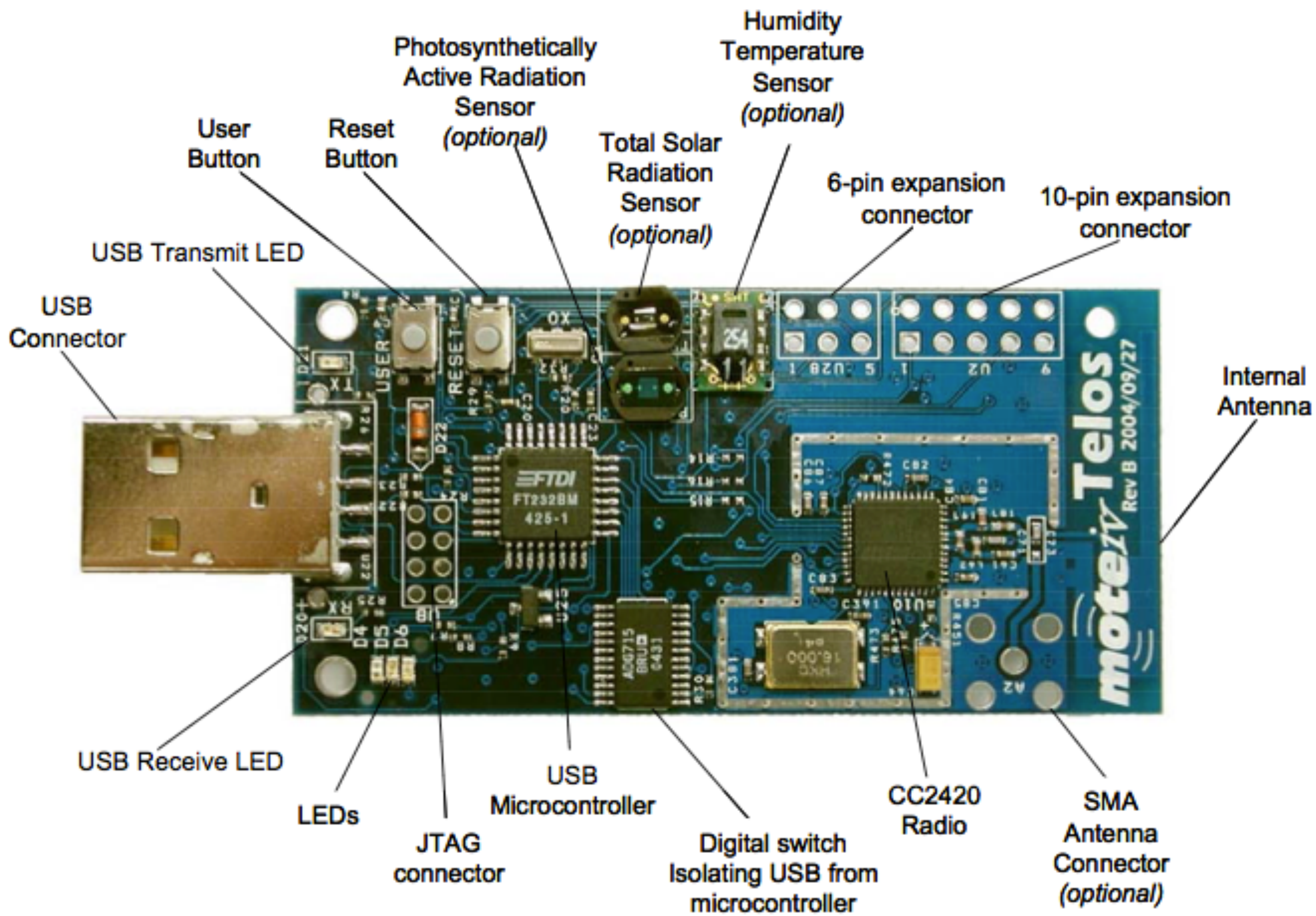
2 MB external flash for data logging

IEEE 802.15.4 compliant RF transceiver

Sensor suite including integrated temperature and humidity sensors

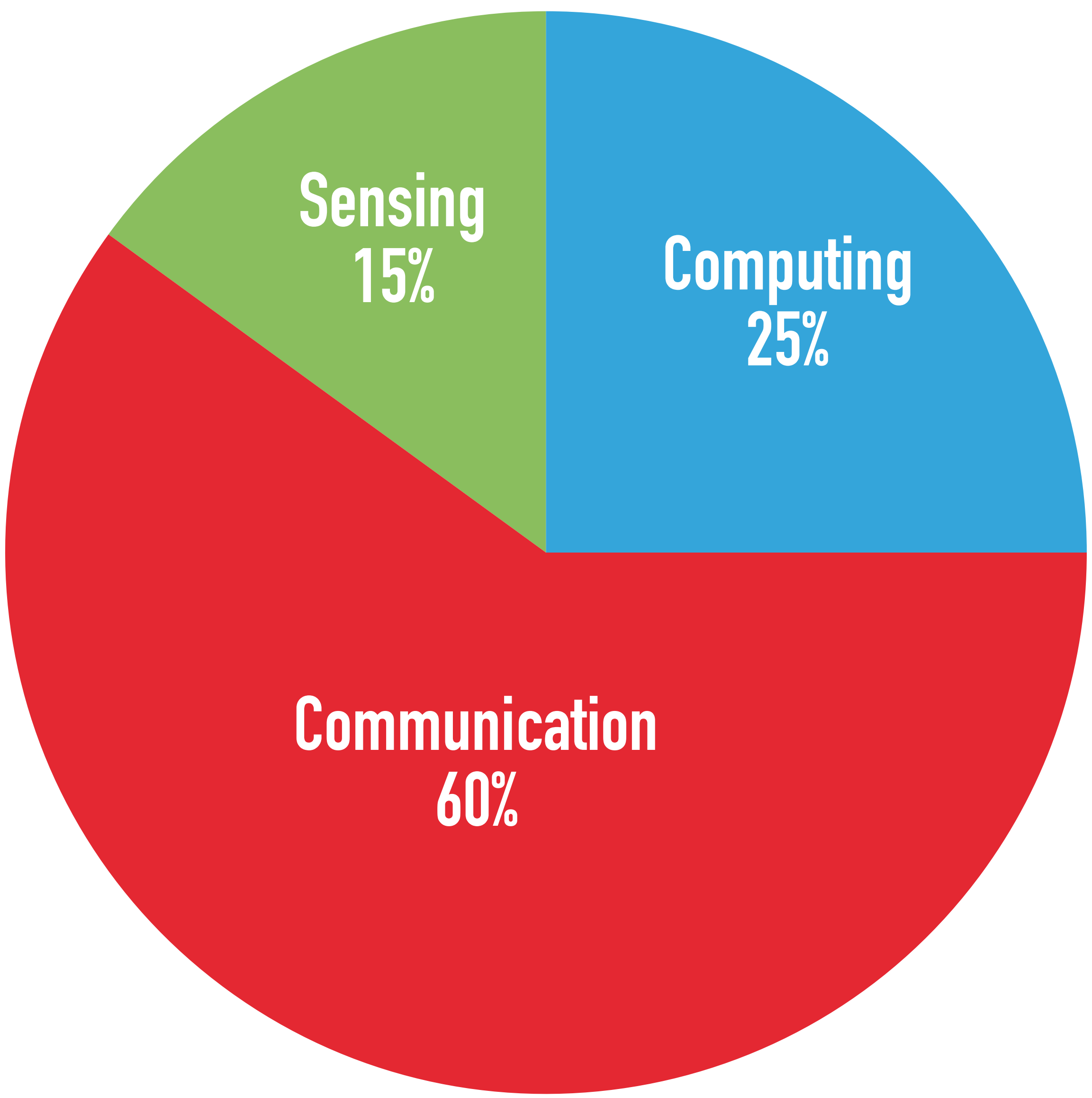
COMPUTATIONAL AND ENERGY RESOURCES

TELOSB



NODE ENERGY CONSUMPTION

The batteries are limited and usually they can't support long tasks (months, sometime years). It's import to save energy in every node component.



SENSING SYSTEM

Every sensors, actuators connected to the nodes plus the software handler to retrieve the data

COMPUTING SYSTEM

Part of this system are the core functions: memory, microcontroller and operating system

COMMUNICATION SYSTEM

The network operations in order to communicate with the other nodes (MAC, ROUTING, SYNC)

NODE ENERGY CONSUMPTION – SENSING

SENSORS

Sensor Type	Power Consumption
Temperature - Humidity	0.5mW - 5mW
Acceleration	3mW
Pressure	10mW - 15mW
Image	150mW
Gas	500mW - 800mW

HOW TO SAMPLE

We can't sample a sensor when we want (especially the most expensive one).
It's important to find the right compromise between **accuracy** and **energy consumption**.

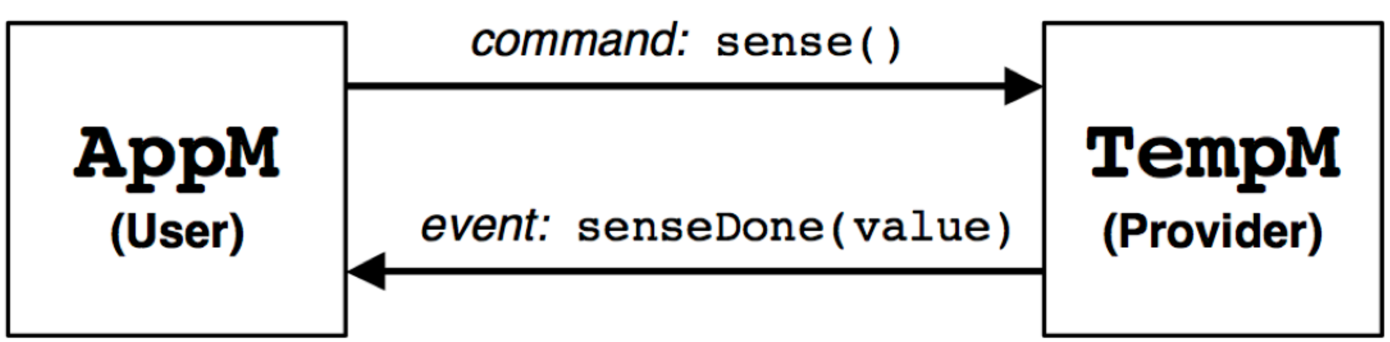
IS IT BETTER TO SAMPLE EVERY SECOND (SHORTER, AND MORE ACCURATE) OR EVERY 60 SECONDS (LONGER, LESS ACCURATE)?

NODE ENERGY CONSUMPTION – COMPUTING

During the computing phase, the energy task is handled by the **hardware** and the designed and developed for this requirements by the **operating systems**.

An interesting example is how **TinyOS** and the programming language **NesC** force the developer to use better design models studied for the **Wireless Sensor Networks** and the **embedded systems** in general. For example:

- Using NesC it's not possibile to allocate **dynamic memory** and **time-consuming loop cycle** are not suggested.
- The OS uses the event paradigm and the **Split-Phase** patter to design software based on the interrupt logic.



NODE ENERGY CONSUMPTION – COMMUNICATION

RADIO CONSUMPTION

The radio transceivers can be in different states:

TRANSMIT AND RECEIVE STATES

The transceiver is transmitting or receiving a packet.

IDLE STATE

The transceiver is ready to receive but it's not doing anything active. Less energy consuming than TX/RX state.

SLEEP STATE

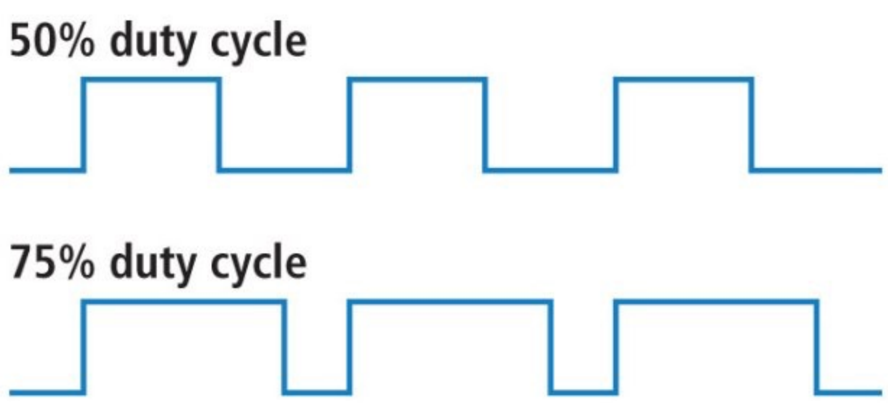
In this state the transceiver can't receive any packet because it is in sleep mode. A **wake-up time** is required to turn on the radio and make it ready. The energy consume is lesser than the other states.

MAGONODEB EXAMPLE

Radio State	Power Consumption
Sleep	1.1 μA
Idle	4.1 mA
RX	14.5 mA
TX	27.7 mA

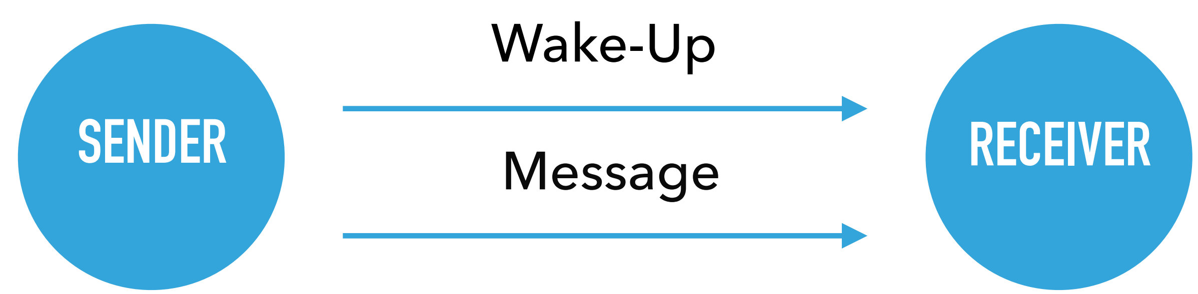
NODE ENERGY CONSUMPTION - COMM (2)

DUTY CYCLE



- ✓ Ready to use with the standard radio
- ✓ State of the art solution with high-level of power energy saving
- ✓ Implemented in most OS
- ✓ Introduces latency in the network
- ✓ Node are not synchronized: long face of idle listesting needed

WAKE-UP RADIO



- ✓ No idle listening
- ✓ Introduces the semantic addressing concept
- ✓ Permits a long network lifetime (until months/years)
- ✓ New hardware
- ✓ The topology inducted by the WUR is shorter than the original one

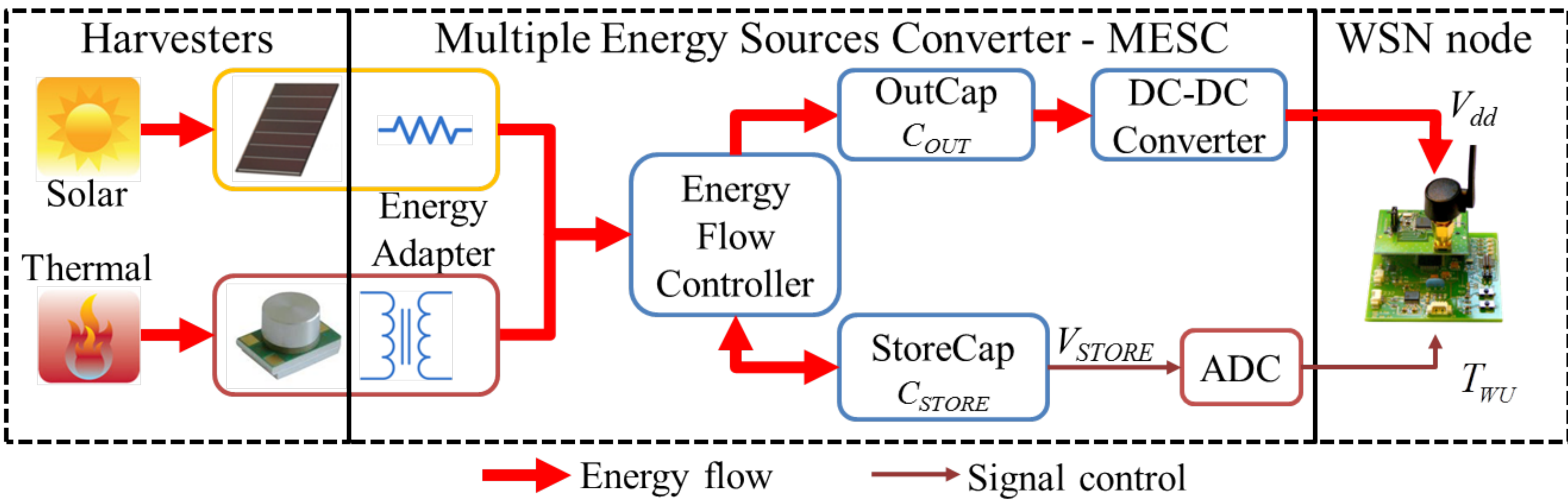
HOW TO INCREASE THE FINITE ENERGIES RESOURCES?

ENERGY HARVESTING

"**Energy harvesting** is the process by which energy is derived from **green external sources**, captured and stored for small devices, like those used in **wearable electronics** and **wireless sensor networks**."

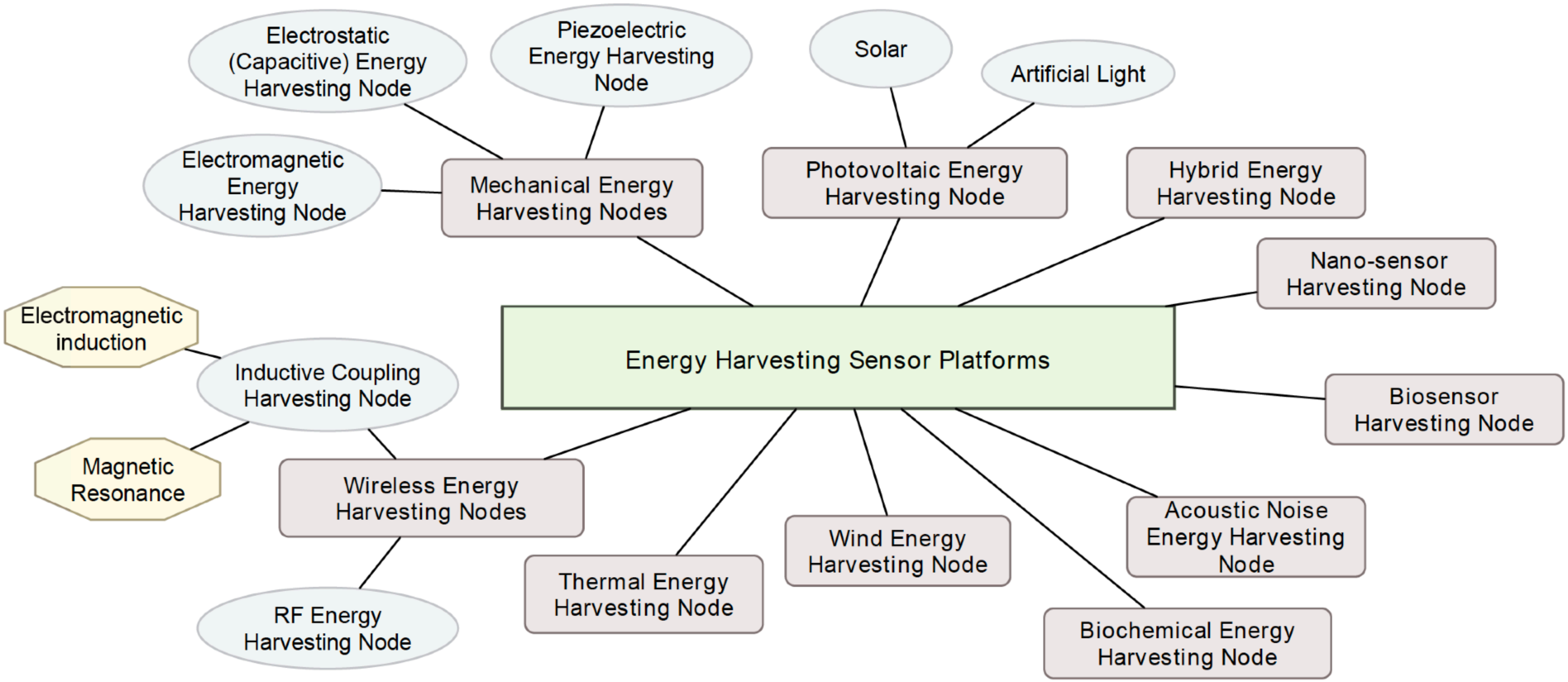
It's possibile to use one or more external sources to sustain the node life.

The energy is either stored in super capacitors and in secondary rechargeable batteries, or it is immediately used.



WHICH ARE THE BEST EXTERNAL SOURCES?

ENERGY HARVESTING – EXTERNAL SOURCES



A GALAXY OF ENERGY RESOURCES BUT NOT ALL OF THEM ARE ABLE TO SUSTAIN THE NODE LIFE TIME

ENERGY HARVESTING – EXTERNAL SOURCES (3)

ENERGY PRODUCTION

Sensor Type	Power Consumption
Photovoltaic	**Outdoor**: 15 mW/cm² **Cloudy Outdoor**: 0.15 mW/cm² **Indoor**: <10 μW/cm²
Thermoelectric	30 μW/cm²
Pyroelectric	8.64 μW/cm²
Piezoelectric	250 μW/cm³ - **Inside the shoes**: 330 μW/cm³
Electromagnetic	**Industrial**: 306 μW/cm³ - 800 μW/cm³ **Human**: 1-4 μW/cm³
Electrostatic	50-100 μW/cm²
RF	**GSM**: 0.1 μW/cm² **WiFi**: 0.01 μW/cm²
Wind	380 μW/cm³
Acoustic Noise	**100 dB**: 0.96 μW/cm³ **75 dB**: 0.003 μW/cm³

IT'S IMPORTANT TO CHOOSE THE RIGHT HARDWARE

Capturing the same energy in a indoor scenario with an indoor optimized solar cell versus a standard solar cell

Indoor cell	Outdoor cell
3,401 mW	**3,993 μW**

ENERGY HARVESTING – EXTERNAL SOURCES (2)

SOLAR ENERGY

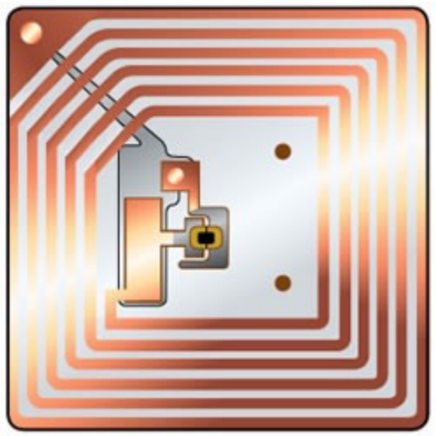
- ✓ One of the most used energy resource
- ✓ High-level of energy acquired
- ✓ Works in **outdoor** and **indoor** scenario
- ✓ The weather conditions are variable
- ✓ In indoor sometimes the energy captured is not enough

WIND ENERGY

- ✓ One of the most used energy resource
- ✓ Good level of energy acquired
- ✓ Not so variable in specific scenarios
- ✓ In some areas there is no wind most of the time
- ✓ It’s not possibile to use in indoor scenario

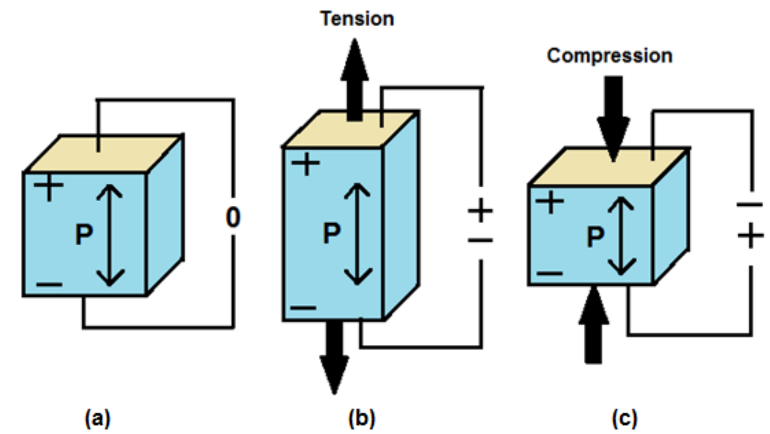
ENERGY HARVESTING – EXTERNAL SOURCES (3)

RF ENERGY



- ✓ Well known because used on **RFID** systems
- ✓ Can be used with other technologies
- ✓ Low level of usable energy
- ✓ Can be used only in specific scenarios and combined with other energy resources

PIEZO ELECTRIC ENERGY



- ✓ Can be used on industrial scenarios
- ✓ Works on particular scenarios like inside a **shoe (runner)**
- ✓ Medium level of energy acquired
- ✓ Only in some scenarios is predictable
- ✓ Can be used only in specific scenarios

ENERGY HARVESTING – STORAGE PROBLEMS

BATTERIES

A battery capacity is assumed to be decreased of the amount of energy required by an operation only when the operation is performed. Real batteries **suffer from self-discharge** and **can be recharged only in the order of 1000 cycles**.

SUPER-CAPACITORS

Energy density is one orders of magnitude lower than electrochemical battery, but they suffer from higher self-discharge. The **super-capacitor leakage** is strongly variable and depends on several factors, including the **capacitance value** of the super-capacitor, the **amount of energy stored**, the **operating temperature**, the **charge duration**.

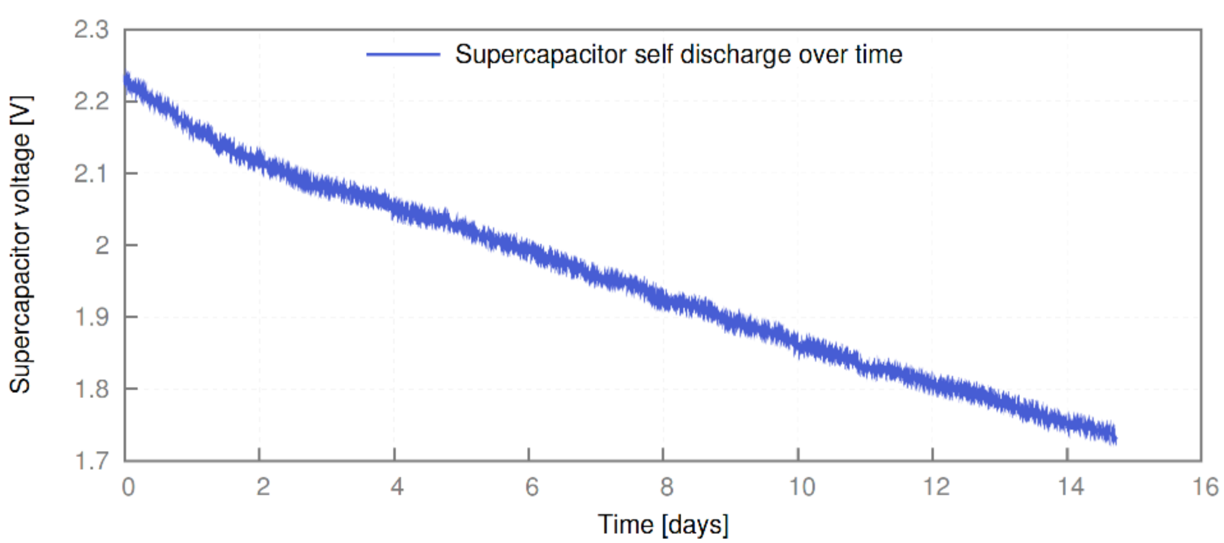


Figure 1.3 Self discharge of a supercapacitor over time.

ENERGY HARVESTING - PREDICTION MODEL

The major problem when using these external resources is the **uncertainty of the availability**.

- Can we harvest some energy?
- Is the amount of energy enough to support a task?

For example the solar energy depends on the **weather conditions** and the same holds for the wind energy. It is also really **tricky to understand** the behavior of other sources like the **piezoelectric systems** or the **RF energy**.

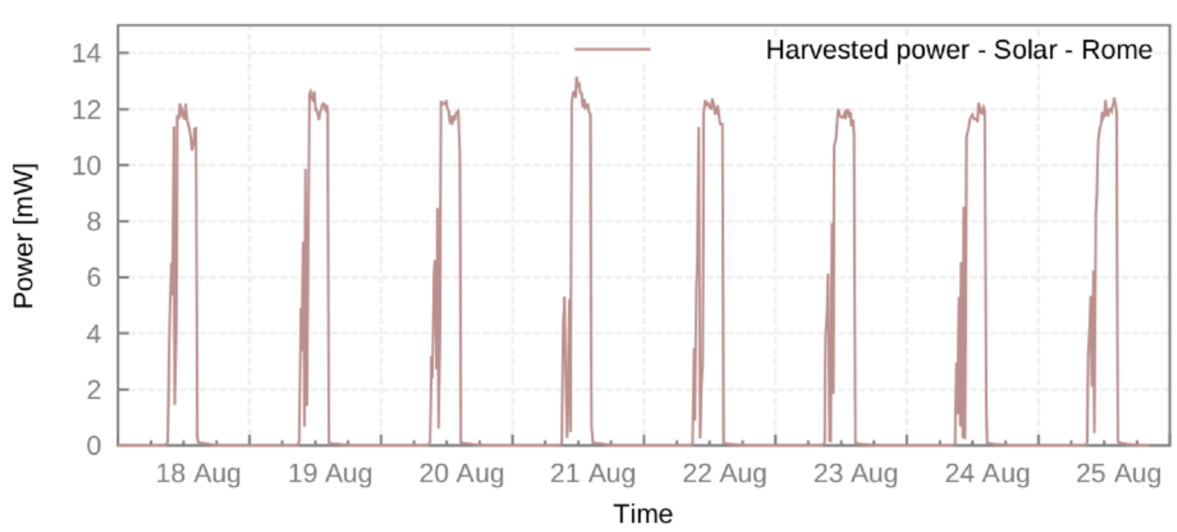
ENERGY HARVESTING – PREDICTION MODEL (2)

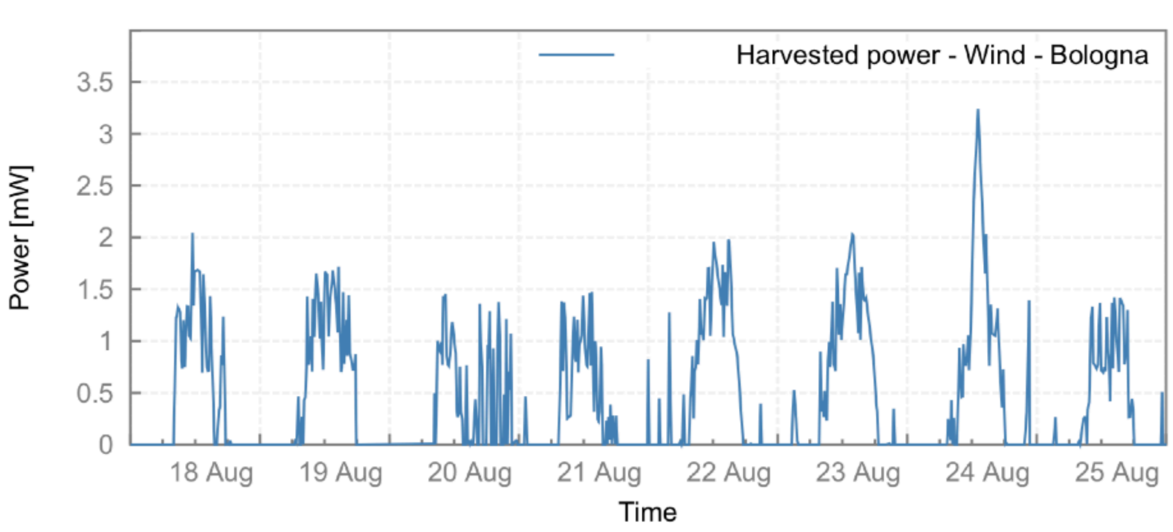
"A prediction model is a way to produce valuable informations to predict the feature using information retrieved from the past."

Different techniques can be used to build a prediction algorithm:

- **statistics inference**
- **linear correlation**
- **heuristics**
- **machine learning** but can be expensive in terms of energy consumption

We will focus on **solar** and **wind** energy prediction because they are the most used resources and mainly because we can produce stronger predictions compared to the other systems.





PREDICTION MODELS - EWMA

EXPONENTIAL WEIGHTED MOVING-AVERAGE

It's one of the first prediction models applied to the solar estimation but the basic idea is old (**1959**) and it was used for other purposes. However the main idea is reutilized from other algorithms.

- The prediction is based on the **knowledge of the past days**.
- Every day is splitted in **N slots** of fixed length (every hour, half hour and so on).
- The estimation method uses the **exponential moving-average** of the past days**.**
- The contribution of the past days **decrease when the information is too old**.

The **energy harvested** at the end of **n-th slot**

Prediction of the slot **n + 1** of the day **d**

Prediction of the slot **n + 1** of the day **d - 1**

$$0 \leq \alpha \leq 1 \qquad \mu_{n+1}^{d} = \alpha \cdot x_n + (1-\alpha) \cdot \mu_{n+1}^{d-1}$$

PREDICTION MODELS - WCMA

WEATHER-CONDITIONED MOVING-AVERAGE

Based on the previous algorithm **EWMA** expands the information used to produce a prediction with the weather notion.

- The day is always splitted in **N slots** of fixed length (every hour, half hour and so on).
- Now it's considered also the **difference** between the **current weather condition** and the **previous days (GAP)**.
- A **matrix E** of size D x n is built, where **D** is the number of days. In every cell the energy harvested is stored on the day d and the slot n: $\mathbf{E_{d,n}}$.
- The energy harvested during the current day is stored in a **vector C** with N elements.
- A **vector M** of size n is also used. The entry $\mathbf{M_n}$ indicates the average energy observed during the time slot n in the last D days:

$$M_n = \frac{1}{D} \cdot \sum_{i=1}^{D} E_{d-1,n}$$

PREDICTION MODELS – WCMA (2)

Energy observed during the time slot n of the **current day**

The **average energy acquired** in the slot n + 1 in the previous D days

$$0 \leq \alpha \leq 1 \qquad P_{n+1} = \alpha \cdot C_n + (1 - \alpha) \cdot M_{n+1} \cdot GAP_n^K$$

The **weather difference** between today and the previous **K** days

IN CASE OF FREQUENT CHANGES IN WEATHER CONDITIONS WCMA'S ERROR IS 20% SMALLER THAN EWMA'S RESULTING ERROR

PREDICTION MODELS - PRO-ENERGY

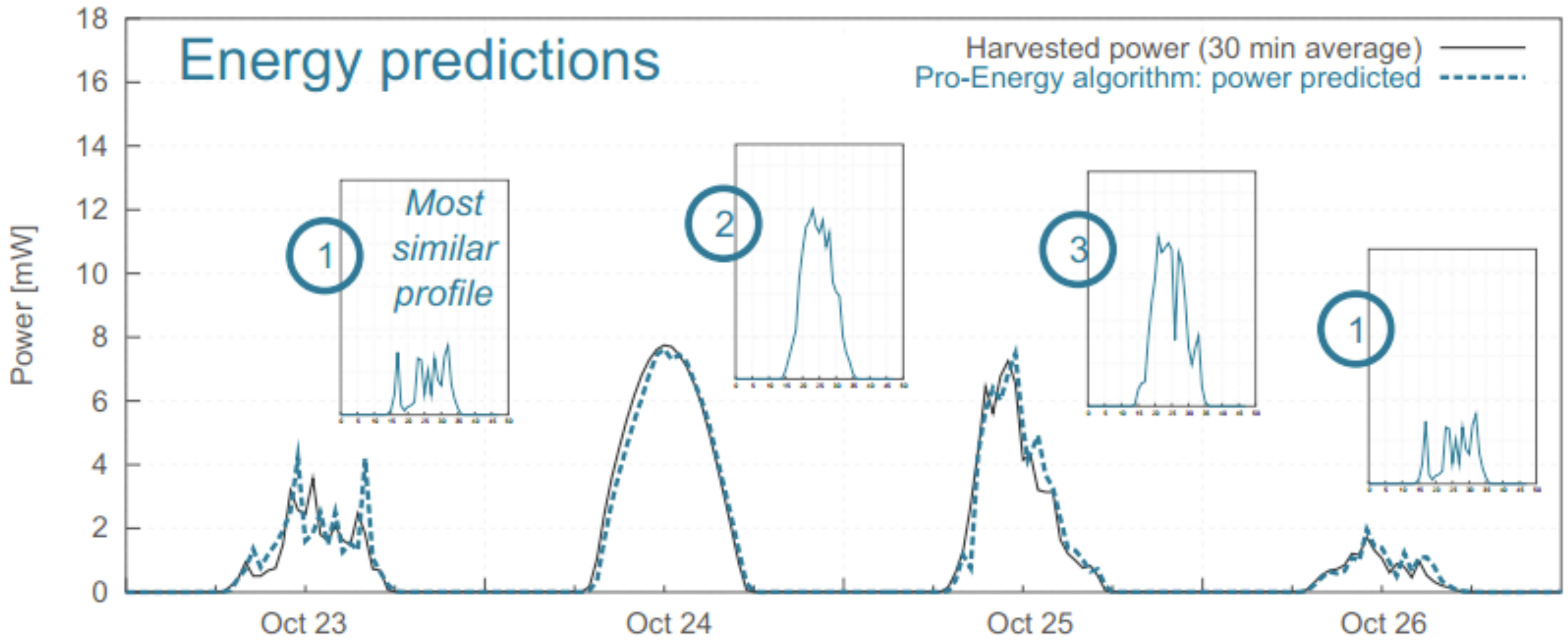
PROFILE ENERGY PREDICTION MODEL

New concept of prediction algorithm developed by the **SensesLab** from our Computer Science Department *(Chiara Petrioli, Dora Spenza e Alessandro Cammarano)*.

- A **multi-source** (solar and wind) prediction algorithm.
- Use the concept of **profile to predict** the short and medium period. A profile is a typical **sunny**, **cloudy** or **rainy day**.
- The day is discretized in **N slots** of fixed length like the other predictors.
- The energy harvested during the current day is stored in a **vector C** with N elements.
- The pool of current profiles stored are represented as a **matrix E** of D x N dimension where D is the number of typical days. The best profile is chosen computing the **Mean Absolute Error (MAE)**.
- The **pool is regular updated** to reflect the weather and seasonal changing. **The old profiles and the infrequently one are discarded** and updated with the new observed.

PREDICTION MODELS - PRO-ENERGY (2)

BEST PROFILE SELECTION



Energy observed during the slot **i** of the **current day**

Energy observed during the slot **i** of the **profile d**

$$E^d = \min \sum_{i=t-K}^{t} \frac{1}{K} |C_i - E_i^d|$$

PREDICTION MODELS – PRO-ENERGY (3)

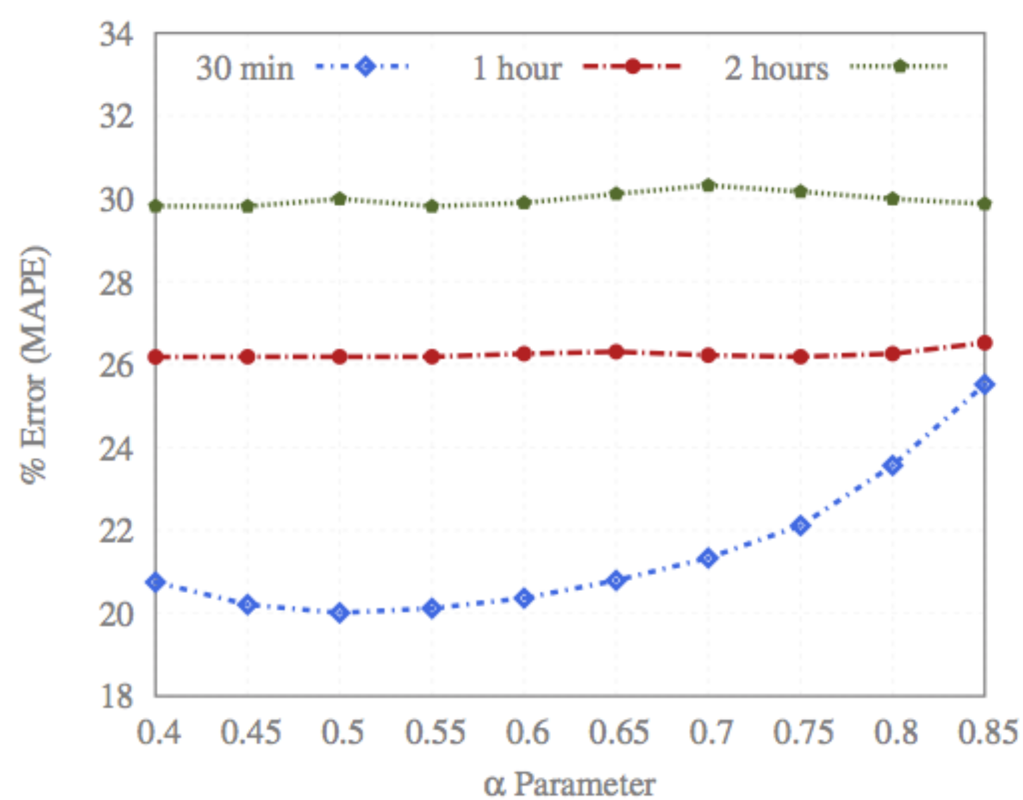
$$0 \leq \alpha \leq 1 \qquad \hat{E}_{t+1} = \alpha \cdot C_t + (1 - \alpha) \cdot E^d_{t+1}$$

Energy observed during the time slot **t** of the **current day**

Energy observed during the time slot t+1 of the **best profile selected**

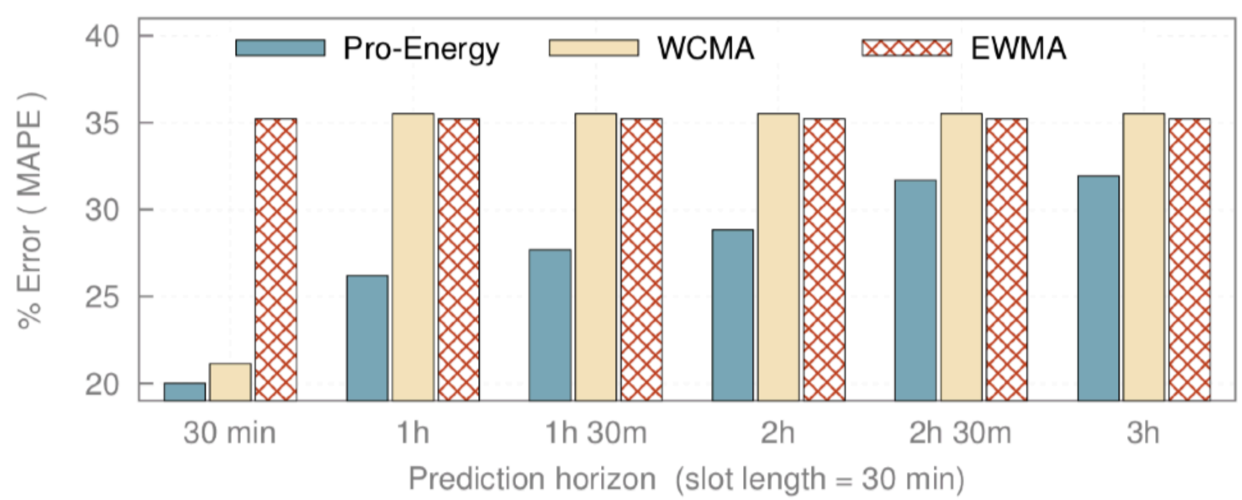
$$MAPE = \frac{1}{T} \sum \left| \frac{\bar{e}_t - \hat{e}_t}{\bar{e}_t} \right|$$

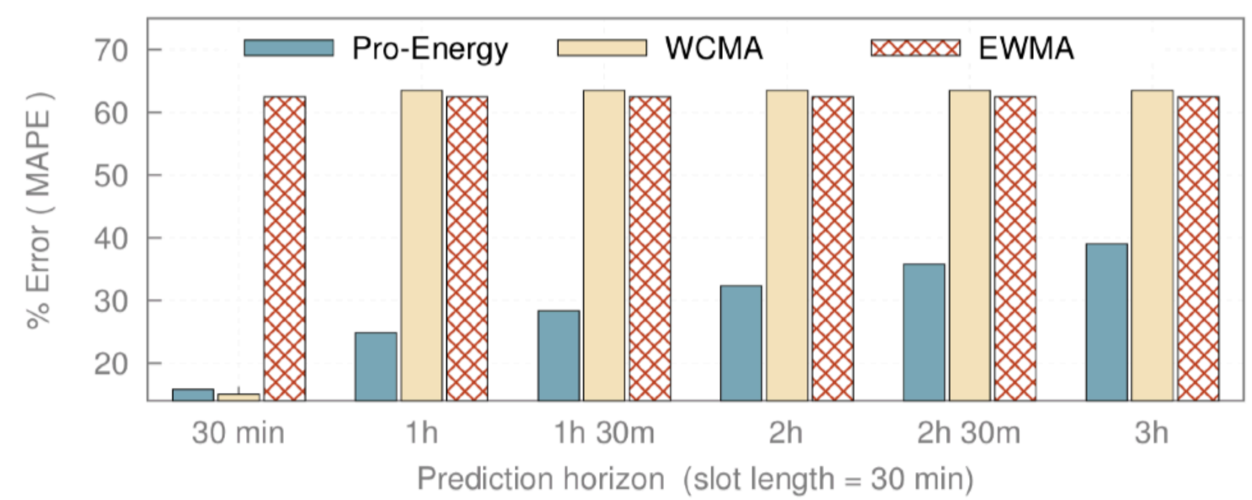
HOW MAPE VARIES ACCORDING TO DIFFERENT VALUES OF THE PARAMETER ALPHA

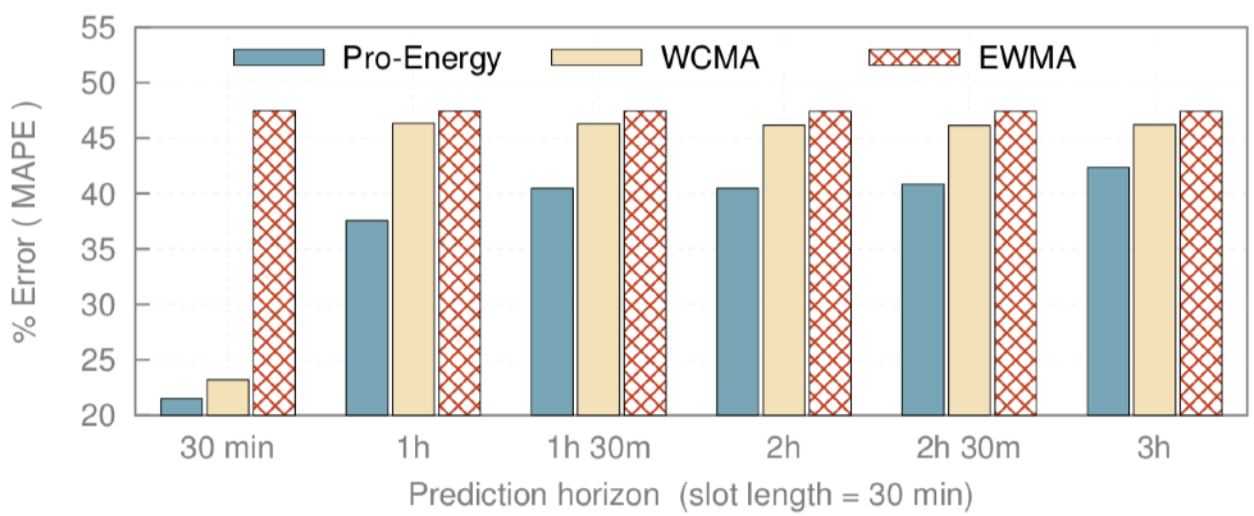


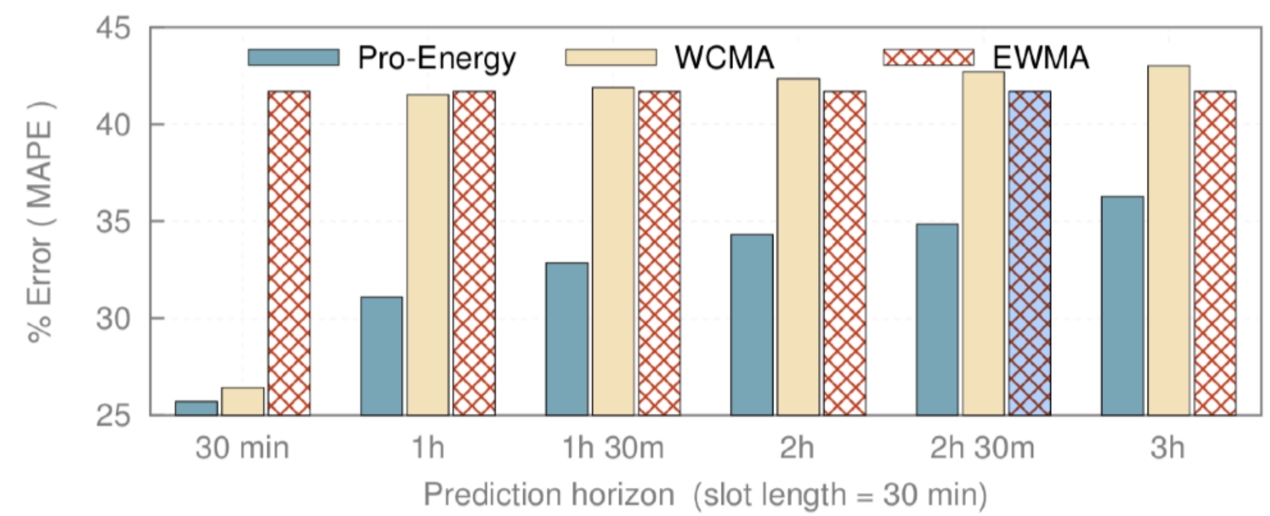
PREDICTION MODELS - PERFORMANCE

OUTDOOR TEST

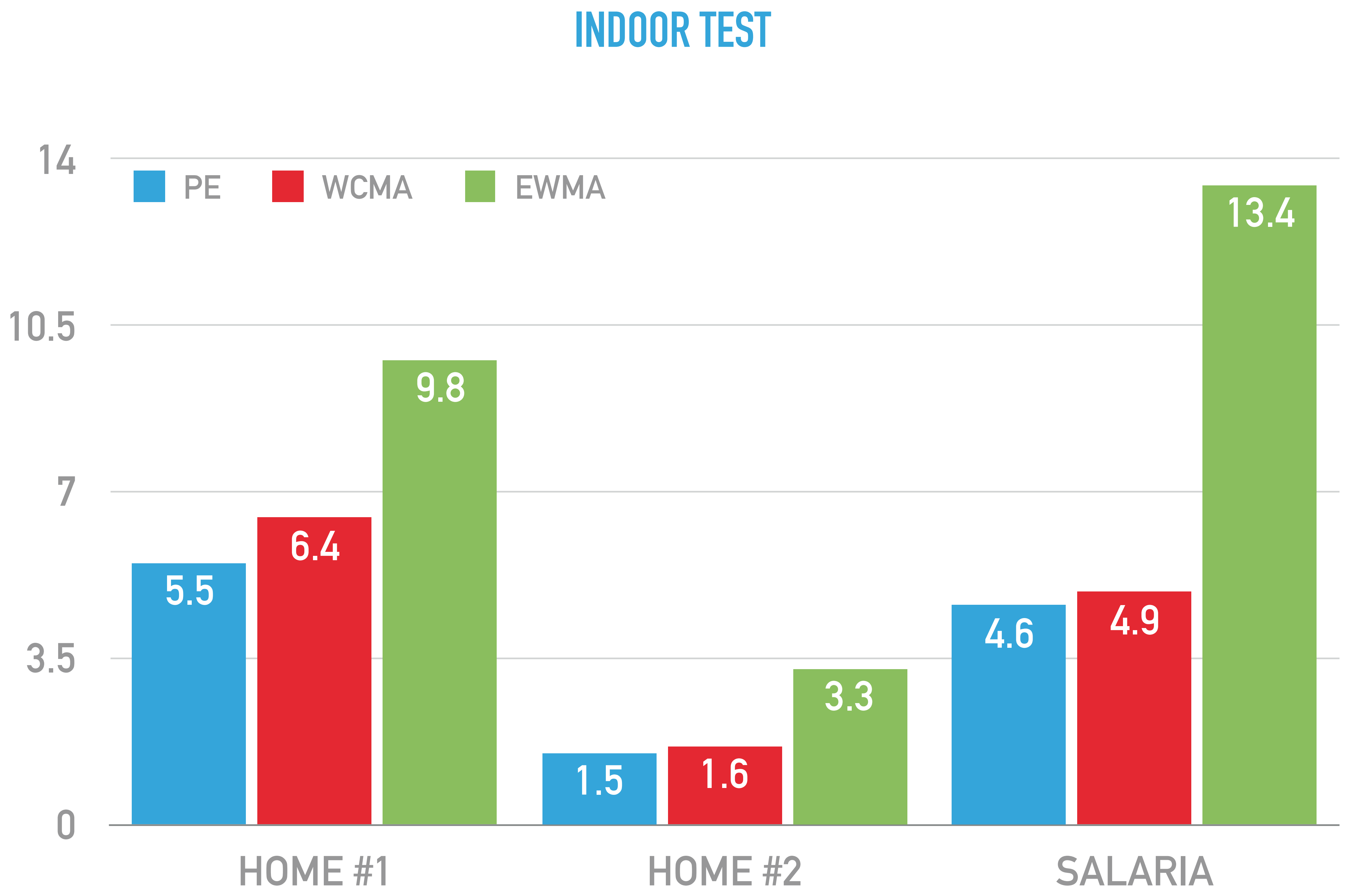




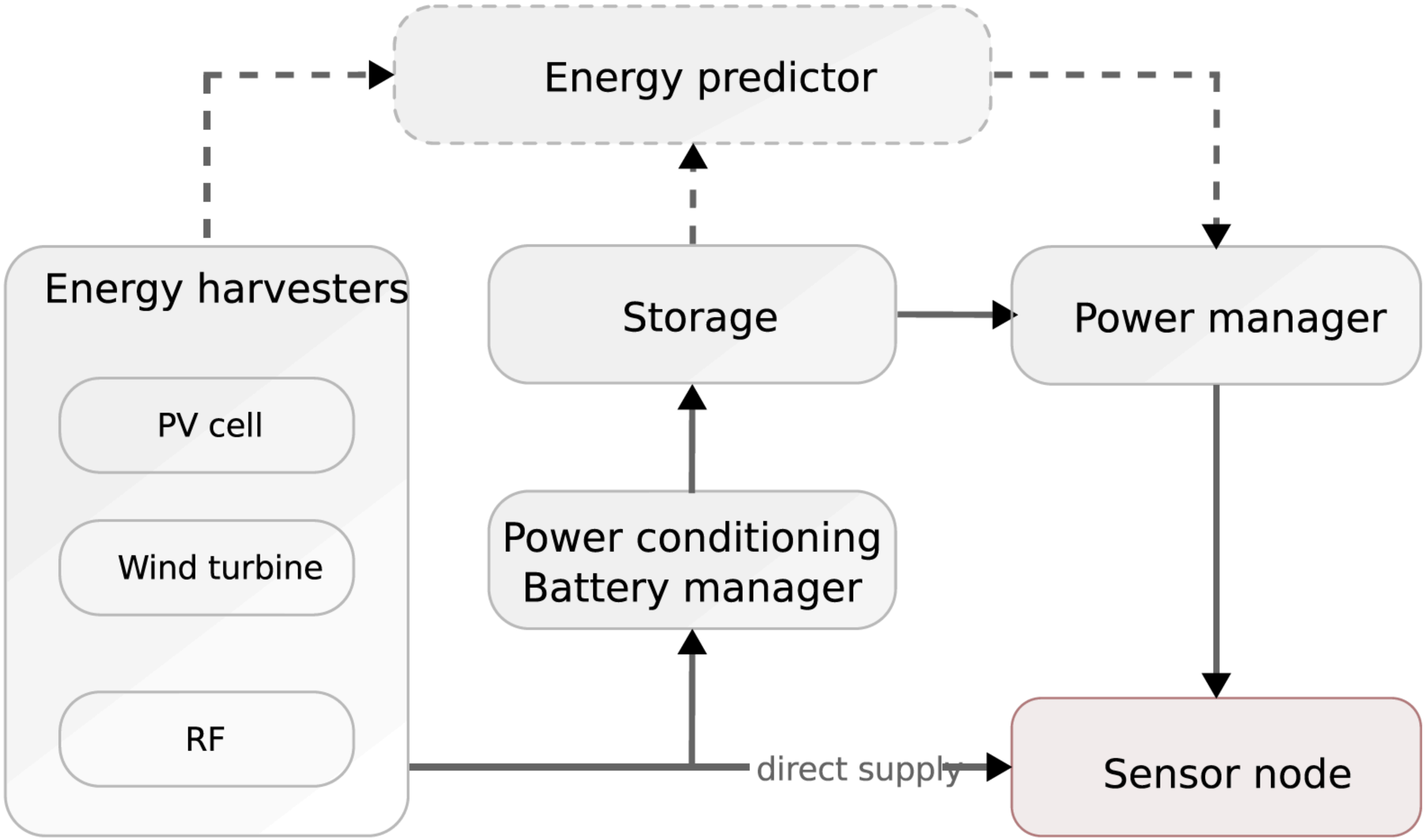




PREDICTION MODELS – PERFORMANCE (2)



ENERGY HARVESTING – NEW NODE ARCHITECTURE



IDEALLY TO ARCHIVE THE BEST ENERGY PERFORMANCES IN TERMS OF LIFETIME WE SHOULD INCLUDE ALSO THE WAKE-UP SYSTEM

ENERGY HARVESTING - GREEN-CASTALIA

ENERGY-HARVESTING-ENABLED FRAMEWORK FOR THE CASTALIA SIMULATOR

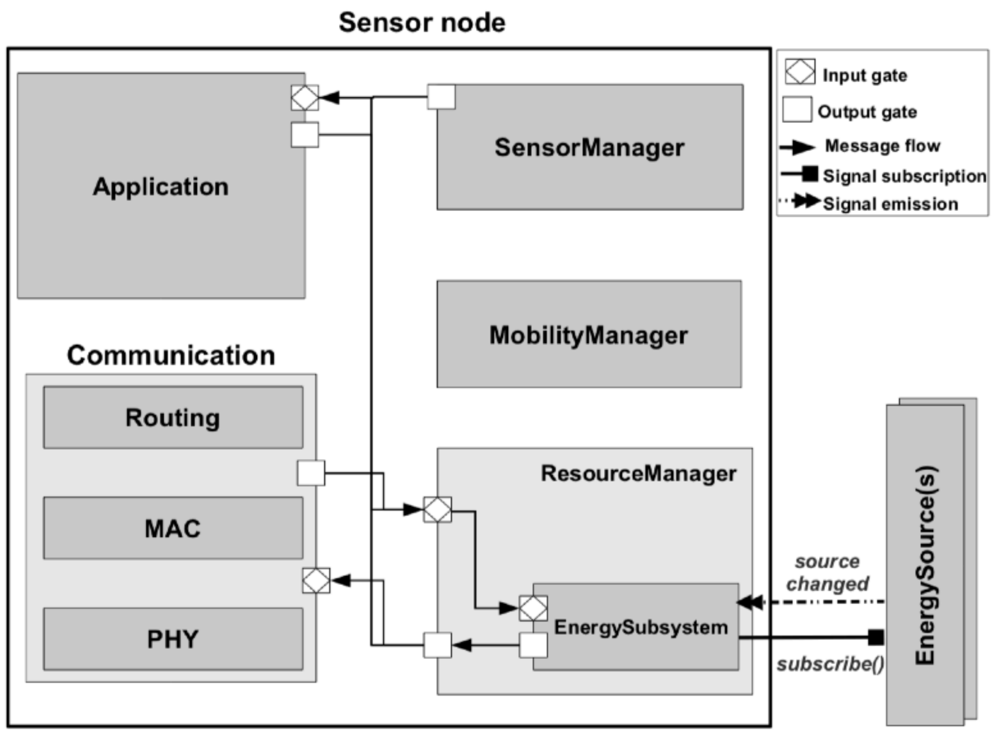


Figure 1: General structure of the SensorNode module in GreenCastalia.

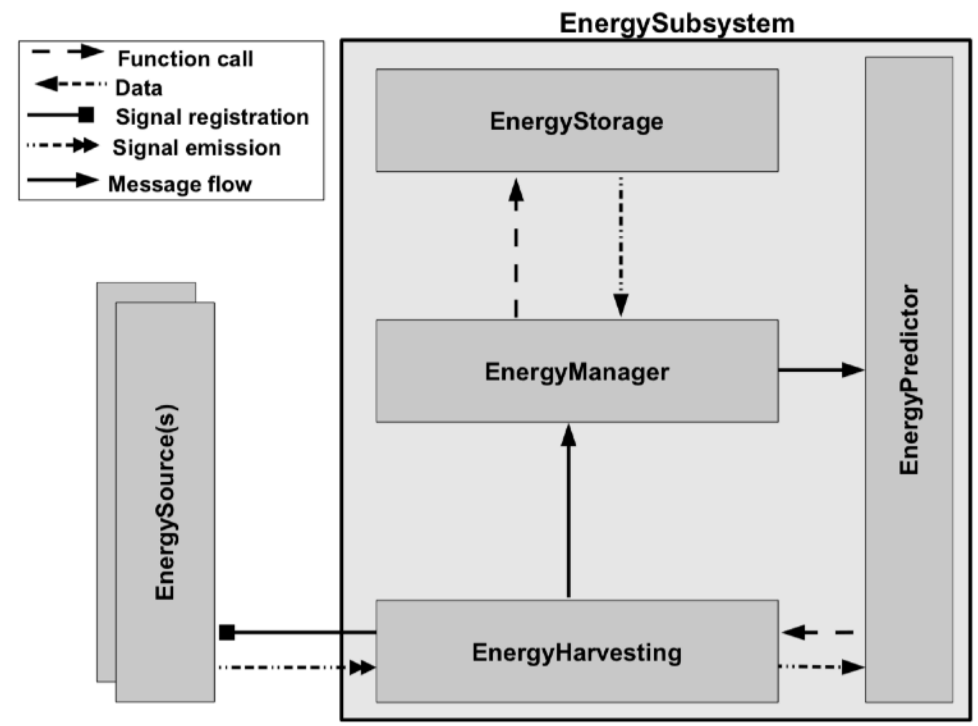


Figure 2: Architecture of the EnergySubsystem module.

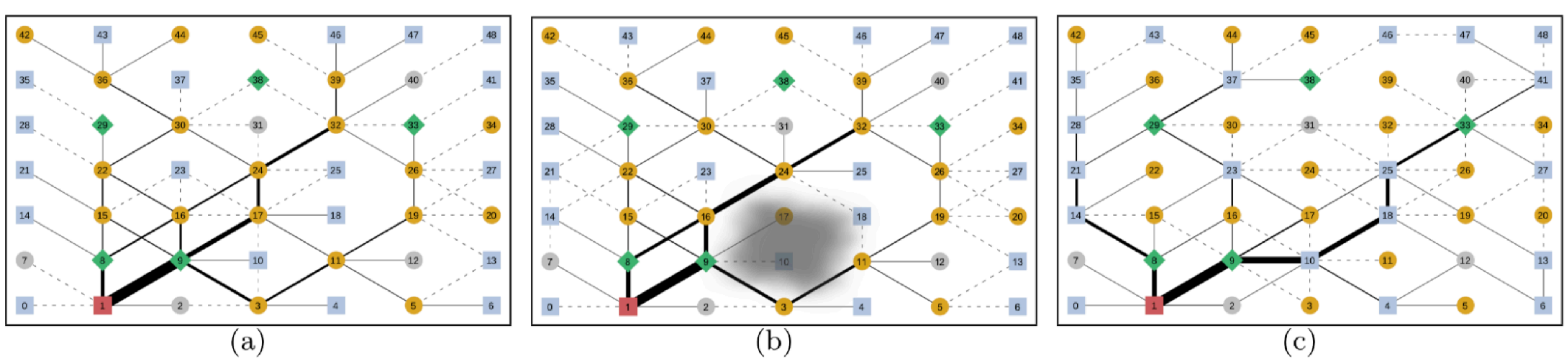


Figure 5: Example of routing paths selected by the harvesting-aware routing protocol: (a) data traffic routing at daytime; (b) effect of localized shadow on routes selection and (c) data traffic at nighttime.

ENERGY HARVESTING – CASE STUDY

STRUCTURAL HEALTH MONITORING OF UNDERGROUND TRAIN TUNNELS

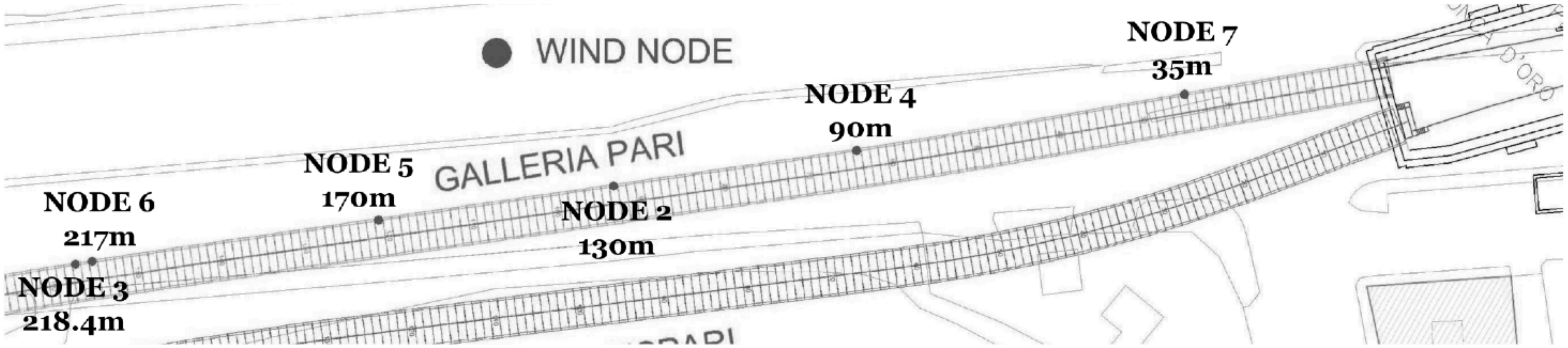
220 m of tunnel with **six Telos B** equipped with **wind micro-turbines**, which collected air-flow data generated by passing trains for **33 days**. The energy harvested from the micro-turbine was then stored in a super-capacitor.

- Temperature
- Humidity
- Strain gauges

ENERGY HARVESTING – CASE STUDY (2)

MEAN ENERGY HARVESTED BY EACH NODE PER TRAIN PASSAGE & NUMBER OF OPERATIONS THAT CAN BE PERFORMED WITH THE GATHERED ENERGY.

Node id	Mean energy harvested per train passage (mJ)	Rx [KB]	Tx [KB]	Flash read [KB]	Flash write [KB]	Humidity	Temperature	ADC reads	Strain measurements per day
7	5.09	2.25	3.32	1.88	1.23	49	16	802	1
4	47.80	21.14	31.12	17.77	11.56	463	158	7530	13
2	51.72	22.88	33.67	19.24	12.51	501	171	8148	14
5	75.68	33.47	49.27	28.15	18.31	734	250	11924	21
6	66.60	29.46	43.36	24.78	16.11	646	220	10493	18
3	132.95	58.80	86.56	49.45	32.17	1290	439	20946	36



HOW CAN WE USE THIS NEW KNOWLEDGE?

APPLICATIONS – SECURITY

As you know **security** is usually **expensive in terms of computation power**. This problem can affect the energy consumption in limited systems such as the nodes used in the Wireless Sensor Networks.

- Is it possible to develop novel security protocols with energy consumption in mind?

This is possible but it is **time consuming to show correctness and robustness** of a newly developed security protocol

THE PRACTICAL WAY IS TO OPTIMIZE CURRENT SOLUTIONS

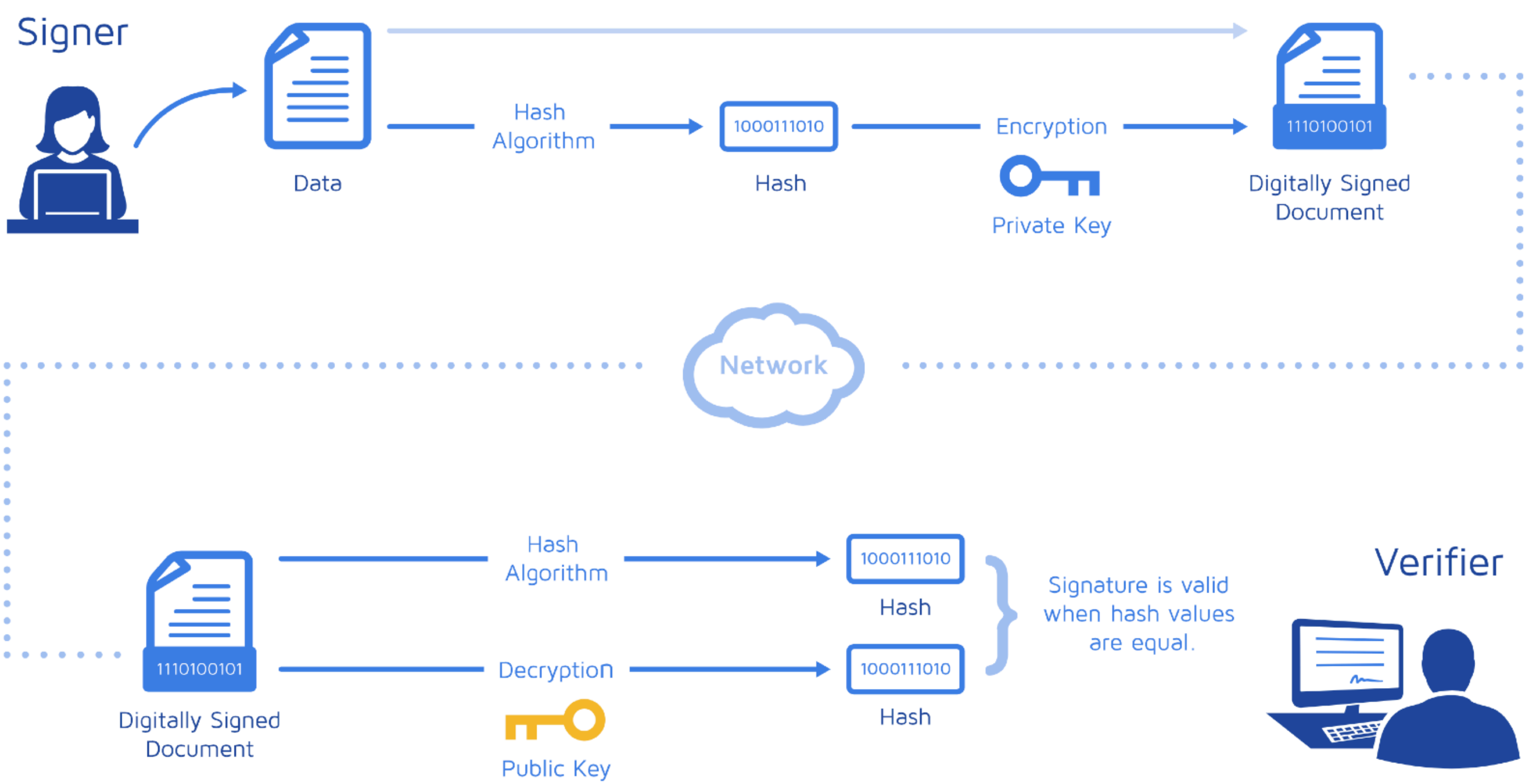
In the next slides we will talk about the **digital signatures** in the IoT/WSN systems to guarantee the identity and especially we will see how to optimize the **Elliptic Curve Digital Signature Algorithm** (ECDSA) using:

- Pre-computation
- Energy Harvesting

APPLICATIONS - DIGITAL SIGNATURES

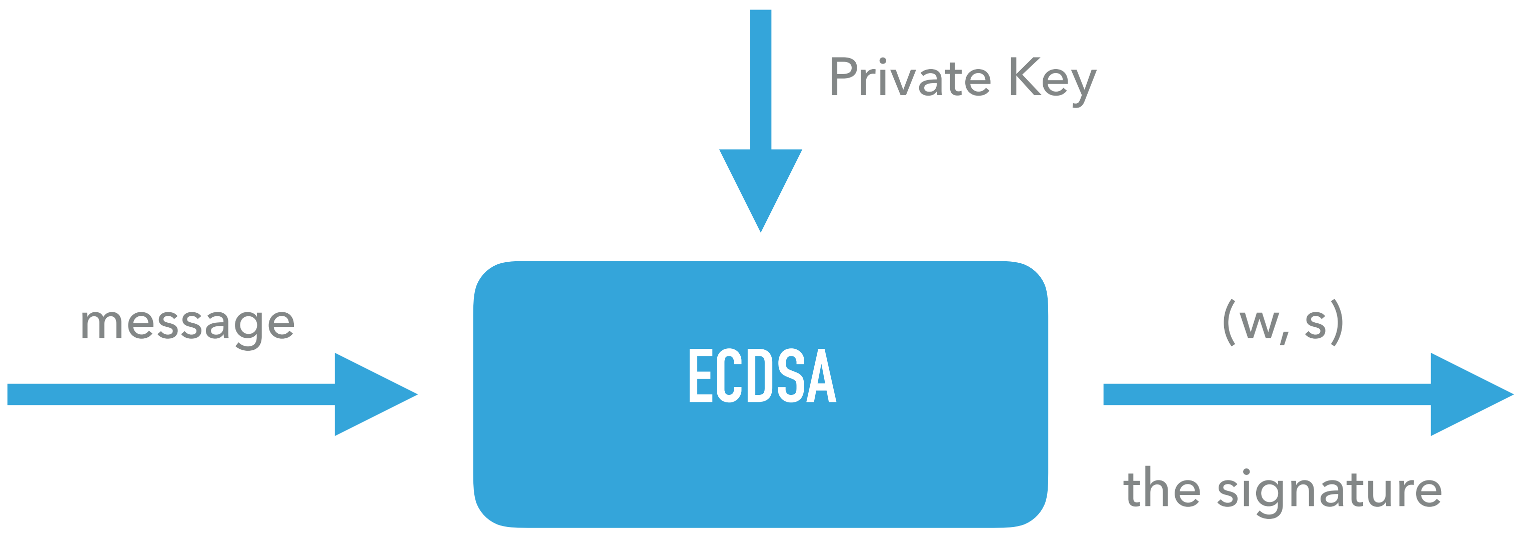
HOW DIGITAL SIGNATURES WORKS

We want to obtain: **AUTHENTICATION**, **INTEGRITY** and **NON-REPUDIATION**



The most used algorithms are **RSA-based**, **El Gamal based** and **ECDSA**.

APPLICATIONS - ECDSA



The most expansive operation is to compute the generation of pairs (r, g^r) where:

- $g \in G_q$ a generator of cycling group of order q
- r a random number $\in [1, q - 1]$
- The elliptic curve point $g = (x_1, y_1)$

The fist possible optimization is to **pre-compute *n* random-chosen pairs** and store theme in a table. When a pair is needed it is possible to select ***k*** of the generated pairs with specific conditions.

HOW TO USE THE ENERGY HARVESTING TO INCREASE THE ENERGY PERFORMANCE?

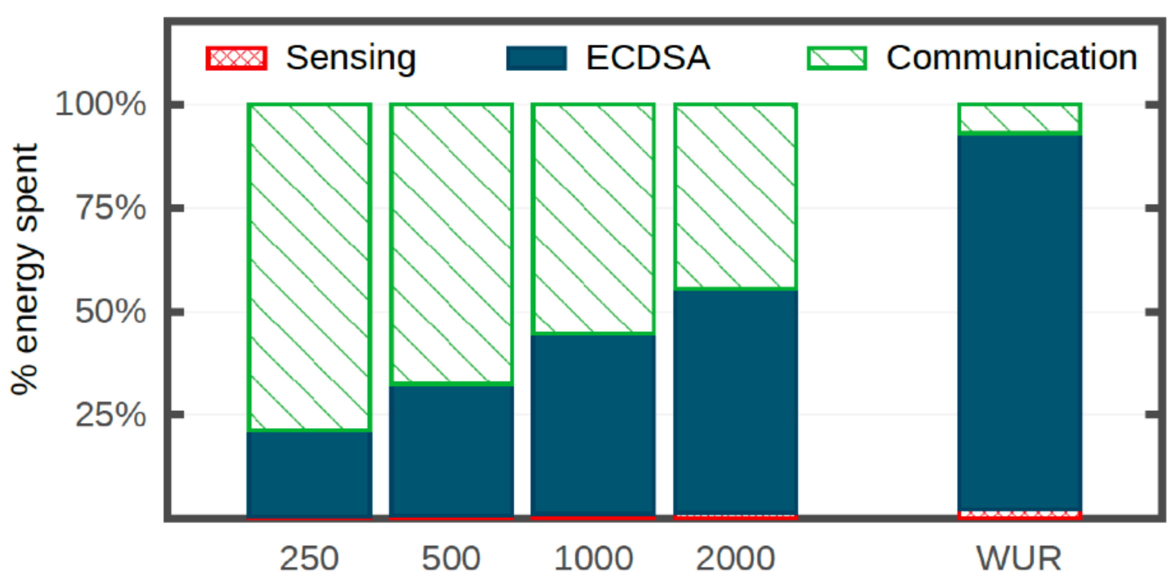
APPLICATIONS – ECDSA WITH EH

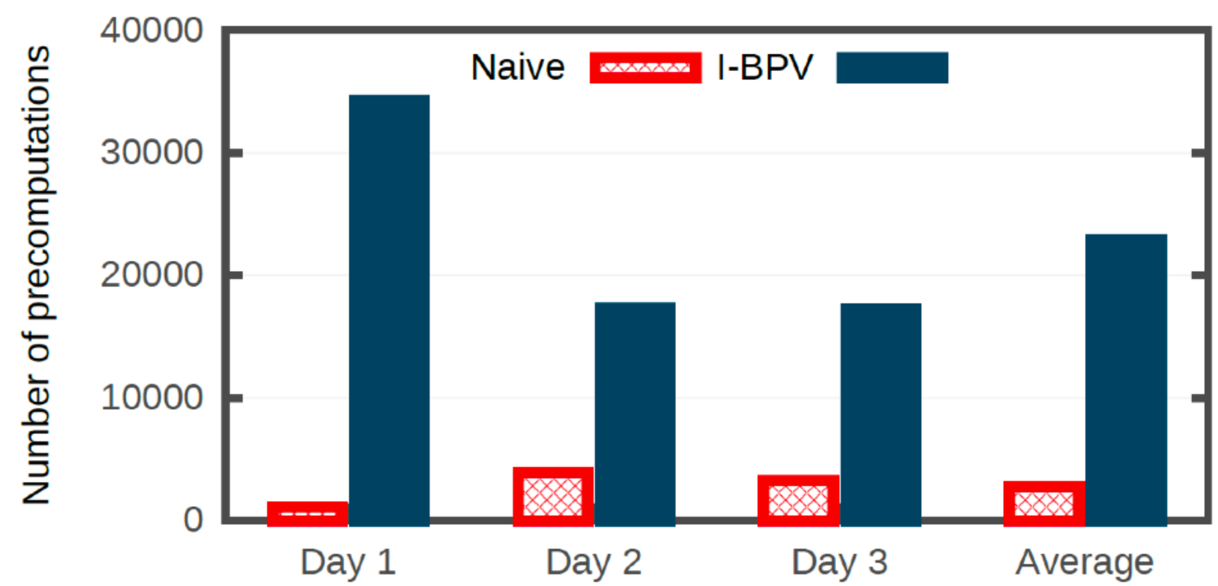
ENERGY PEAK

"An energy peak occurs whenever a node is harvesting power at a rate that exceeds its current power consumption or more generally exceeding a given charging level threshold."

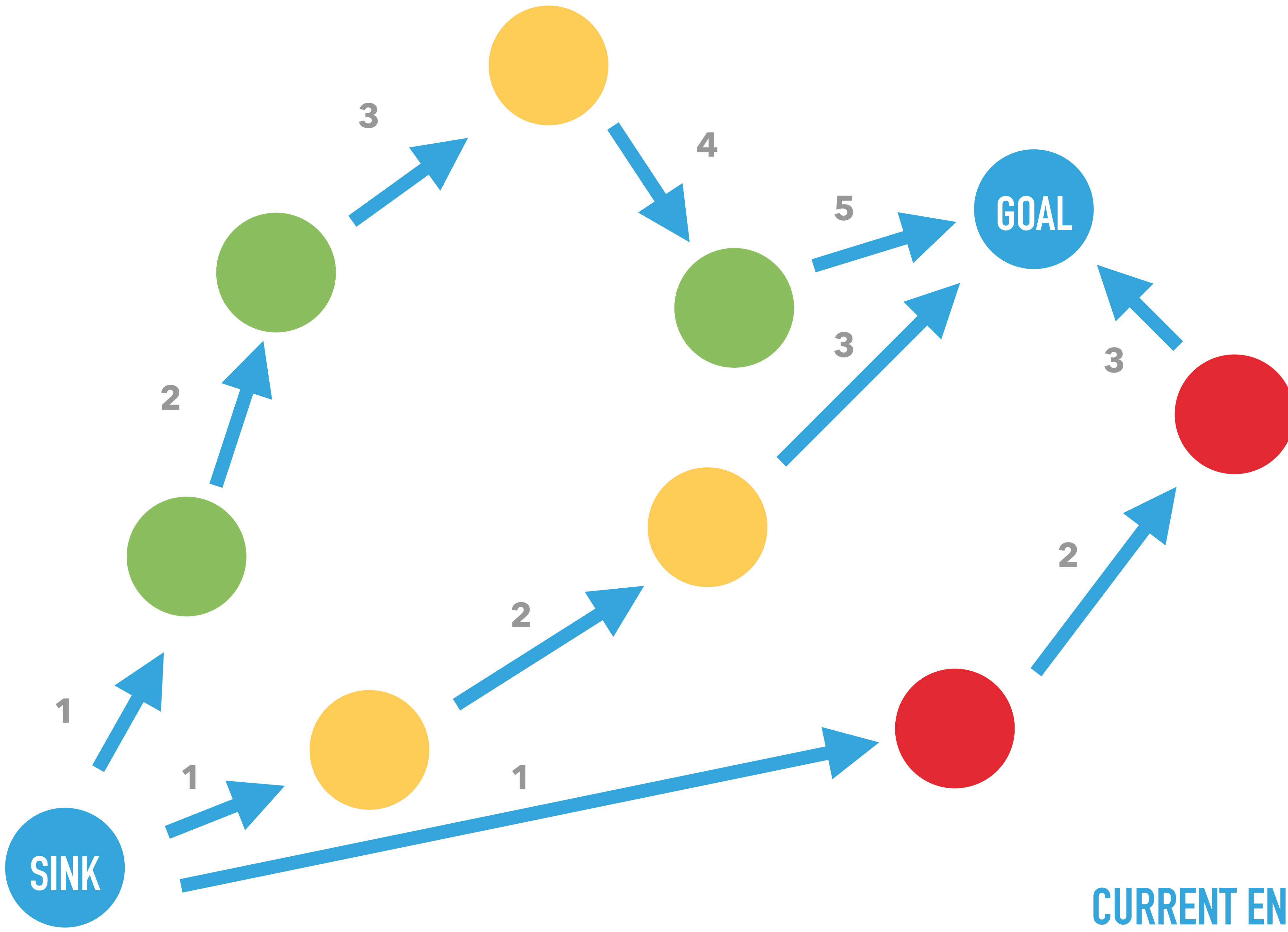
It's possible to use these energy peaks to pre-compute the cache table without losing important energy available for other tasks.

SOME RESULTS





APPLICATIONS – ROUTING



CURRENT ENERGY LEVEL

FUTURE ENERGY

APPLICATIONS - ROUTING (2)

E-WME

The cost of each node is an exponential function of the node **residual energy**, a linear function of the **transmit and receive energies**, and an inversely linear function of **the harvesting power rate**.

Cost function it is based on: **residual energy**, its **battery capacity**, it **harvesting power rate** and the **energy required for receiving and transmitting packets**.

DEHAR

The shortest paths to the sink it is based on the **hop count** and the **energy availability of the nodes**. A **local penalty** is assigned to each node, it is inversely proportional to the **fraction of energy available to the node**.

Cost function is based on: **the local penalty** that is combined with **distance from the sink** to define the node energy distance.

GREES

Each node maintain its one-hop neighbor information including the **neighbors location**, **residual energy**, **energy harvesting rate**, **energy consuming rate**, and **wireless link quality**.

Cost function is based on two factors: the **geographical advance** and the **energy availability of the receiving node**.

APPLICATIONS - TASK ALLOCATION

IT IS IMPORTANT TO DYNAMICALLY SCHEDULE TASKS

Task scheduling protocols can be categorized in two classes: **node tasks** and **network tasks**.

NODE TASK

Tasks such as **sensing**, **computing**, and **communication** can be considered node tasks.

NETWORK TASK

Examples of network tasks are **routing**, **leader election**, **cooperative communication.**

DUE TO DIFFERENT CHARACTERISTICS OF NODE AND NETWORK TASKS, THEY NEED DIFFERENT SCHEDULING AND ENERGY BUDGETING ALGORITHMS

In the next slides we will talk about the sensor mission assignment and **EN-MASSE** a model developed by our research group and the Penn State University. The problem consists to dynamically assign resources reaching a goal (e.g. sensing an area).

APPLICATIONS – TASK ALLOCATION: EN-MASSE

"**Decentralized heuristic** for **sensor-mission assignment** which takes into account the characteristics of an **energy harvesting system** to decide which node should be assigned to a particular mission at a given time."

- Able to handle **hybrid energy storage systems** (multiple systems)
- Uses an **energy prediction model to estimate the energy** a node will receive from the ambient source and to classify missions
- **Adapt its behavior** according to the **current** and **expected energy** availability of the node, while **maximizing** the efficient **usage of the energy harvested**
- The algorithm splits the area in different locations called $\mathbf{l_i}$ and assigns a **mission leader** for every location that coordinates the process of assigning nodes to a mission.
- Each time a new mission arrives in the network, the leader advertises mission information as **mission location**, **profit and demand**, to its two-hop neighbors, thus starting the *bidding phase*.

APPLICATIONS – TASK ALLOCATION: EN-MASSE (2)

BIDDING PHASE

During this *bidding phase*, **each node** receiving the mission advertisement from the leader, **autonomously decides whether to apply** for the mission depending on the following factors**:**

- The **current energy level** of the node **battery** and **capacitor**
- The **energy cost of the mission**
- The **future energy availability** (**PRO-ENERGY**)
- The **profit of the mission**
- The **utility offered by the node** with respect **to the mission** demand
- The target **lifetime of the network**

A mission can be classified as:

FREE	RECOVERABLE	CAPACITOR SUSTAINABLE	BATTERY REQUIRED

APPLICATIONS - TASK ALLOCATION: EN-MASSE (3)

FREE

The node **super-capacitor is full** and the energy cost is expected to be **fully sustained by the energy harvested** during their duration.

RECOVERABLE

Are those whose energy cost **can be sustained** using the energy stored in the **super-capacitor**. Energy cost can be **recovered in a small period of time.**

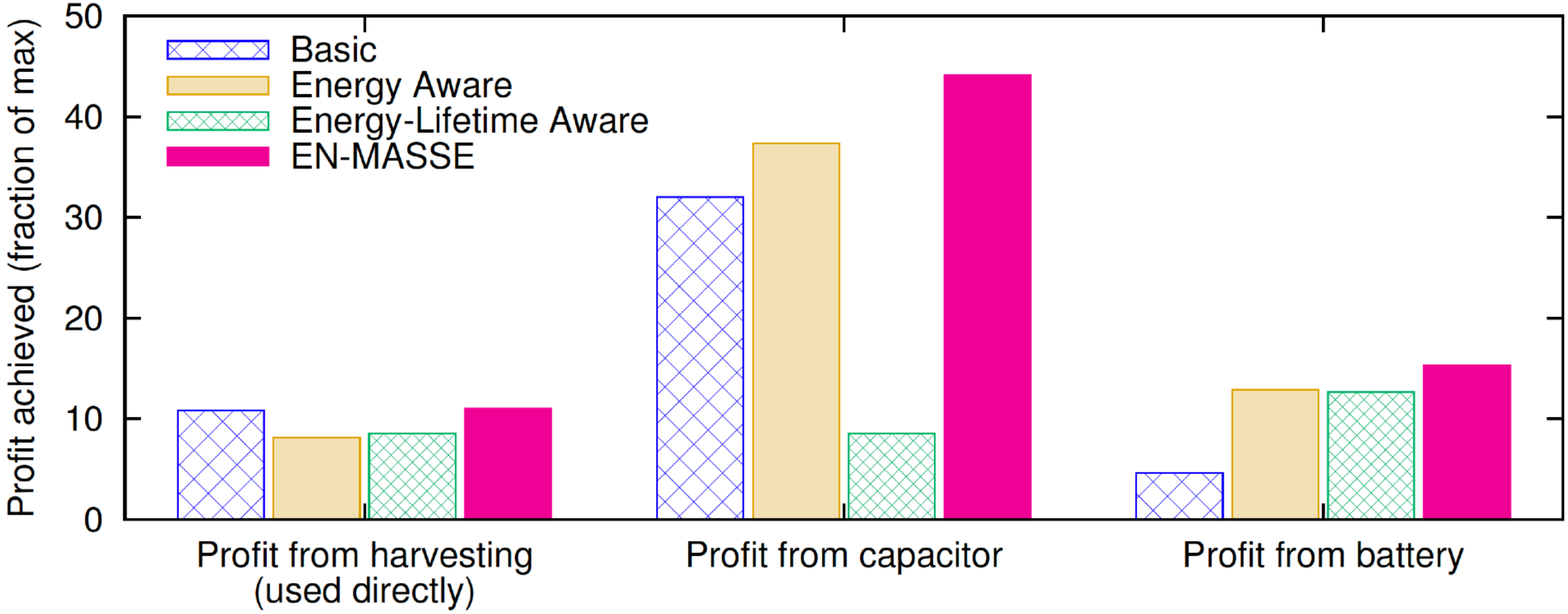
CAPACITOR SUSTAINABLE

Are those whose energy cost **can be sustained** using the energy stored in the **super-capacitor**. Energy cost cannot be **recovered in the near future.**

BATTERY REQUIRED

Are those whose energy cost must be **totally or partially supplied by the battery**.

APPLICATIONS – TASK ALLOCATION: EN-MASSE (4)



NEW SUBSIDIARY FORMATIVE ACTIVITY

In the next semester a new **SUBSIDIARY FORMATIVE ACTIVITY (ATTIVITÀ FORMATIVA COMPLEMENTARE)** will be offered:

DESIGN AND DEVELOP AN EMBEDDED SYSTEM

Lectures on IoT/WSN platforms and operating systems, sensors and actuators, C development with lab sessions and a final project.

Further information in the next months or feel free to contact me.

W • S E N S E

INTEGRATED CABLELESS SOLUTIONS

RESOURCES

[1] S. Basagni, M. Y. Naderi, C. Petrioli and D. Spenza "Wireless Sensor Networks with Energy Harvesting" Link

[2] A. Cammarano, C. Petrioli and D. Spenza "Online Energy Harvesting Prediction in Environmentally-Powered Wireless Sensor Networks" Link

[3] A. Cammarano, C. Petrioli and D. Spenza "Energy-harvesting WSNs for structural health monitoring of underground train tunnels" Link

[4] G. Ateniese, G. Bianchi, A. Capossele, C. Petrioli and D. Spenza "Low-cost Standard Signatures for Energy-Harvesting Wireless Sensor Networks" Link

[5] T. La Porta, C. Petrioli, D. Spenza "Sensor-mission Assignment in Wireless Sensor Networks with Energy Harvesting" Link

QUESTIONS

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