UNIVERSITY OF SALENTO
Department of Engineering for Innovation

Research Activities at CREA
UNIVERSITY OF SALENTO

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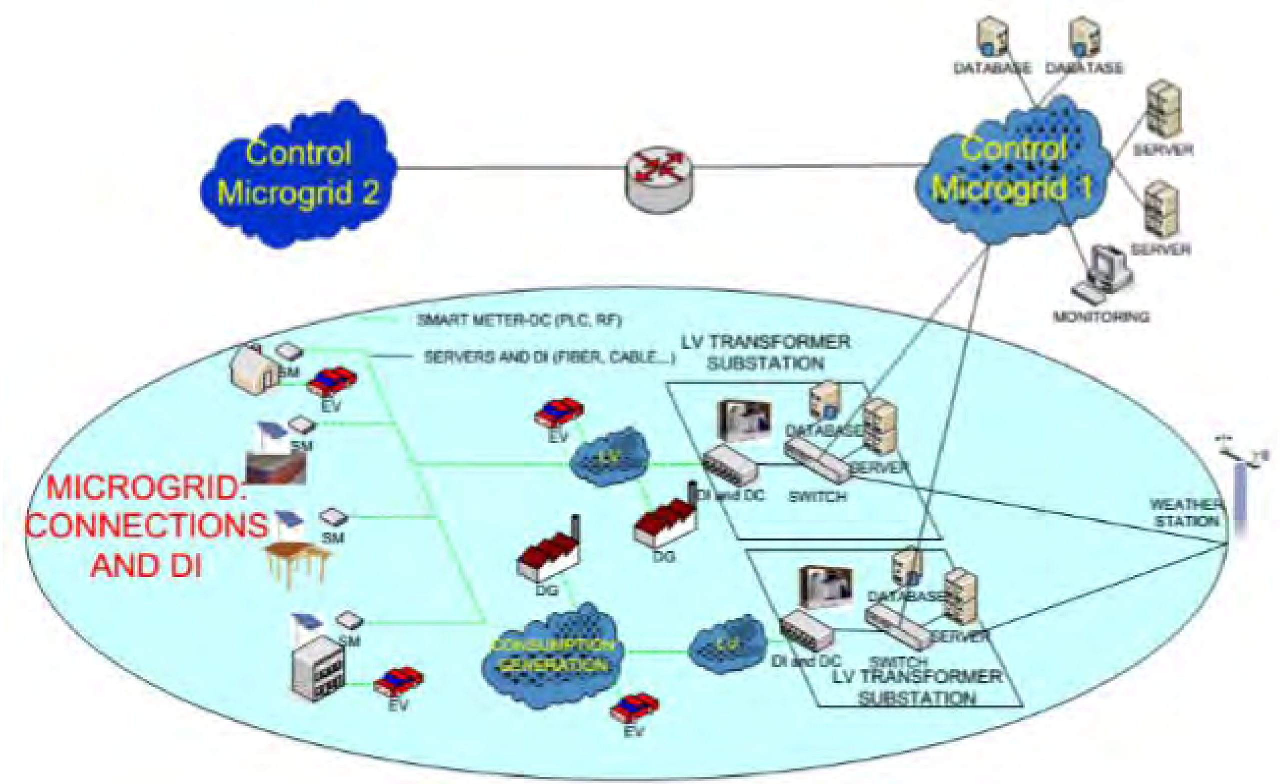
National Study Day on Mini Grids for Urban, Rural and Industrial Development, Rome 21 June 2018

Renewable energy forecasting

Load and Renewable Energy Forecasting for a Microgrid

- **Forecasting algorithm in a microgrid**
  - To predict the **demand of the loads** in the microgrid network
  - To predict the **power generated by renewable energy** connected to the network for the near future.



Load and Renewable Energy Forecasting for a Microgrid

- **Forecasting algorithm in a microgrid**
  - To predict the **demand of the loads** in the microgrid network
  - To predict the **power generated by renewable energy** connected to the network for the near future.

- This is necessary for determining how much power is used from the controllable resources such as **Energy Storage Systems (ESS),** diesel generators, micro-turbines or gas turbines.

- The **optimization algorithm of the microgrid EMS** utilizes the load and renewable energy forecasts to schedule in advance the power generated by distributed generators (DGs) or charged/discharged by storage devices, in an optimal manner.

Forecasting algorithms

RENEWABLE ENERGY FORECASTING can be categorized from **time horizon point of view** into hour-ahead, day–ahead or intra-hour types of forecasts.

Microgrid applications: generation and load forecasts required are usually **short-term forecasting (*hours or days in advance)***

Physical approaches model physical atmospheric phenomenon as part of the solar irradiance prediction using **Numerical Weather Prediction (NWP)** methods or sky imagery.

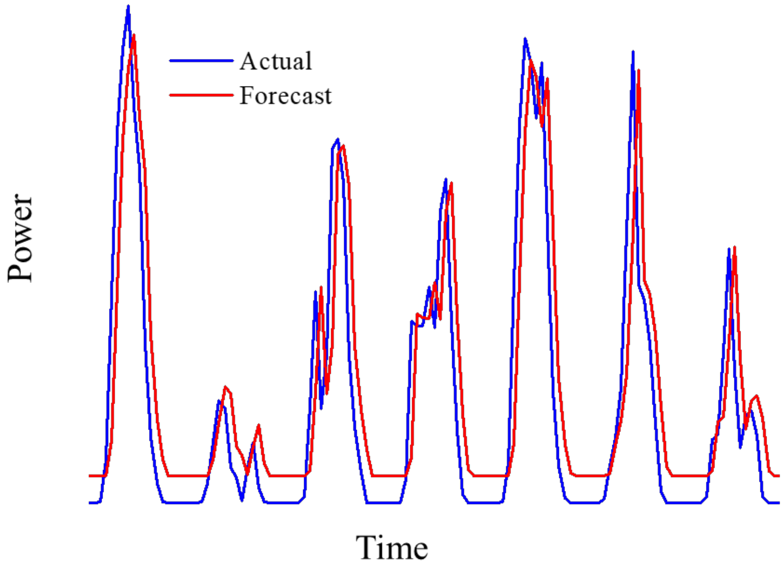
Statistical approaches rely on an historical database of solar power generation, and the respective weather conditions.

Research Activities at UNISALENTO

NOVEL PHOTOVOLTAIC FORECASTING MODELS

Development of innovative forecasting models for wind and solar energy based on data-driven approaches.

- **Improvements of the prediction models with more accurate results and lower error are necessary for future development of the microgrids projects**



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NOVEL PHOTOVOLTAIC FORECASTING MODELS

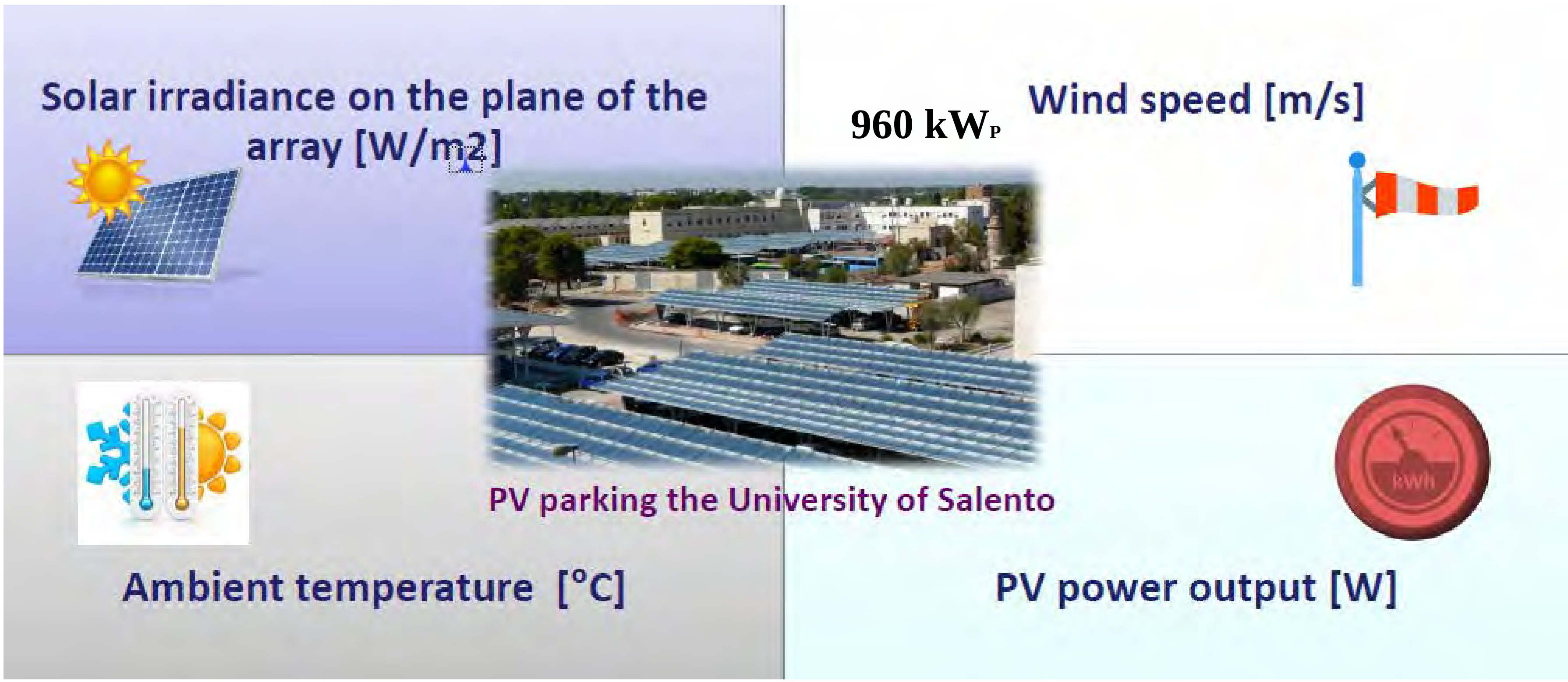
Development of innovative forecasting models for wind and solar energy based on data-driven approaches.

- **TO IMPROVE THE RES POWER FORECASTING MODELS ACCURACY**

Implementation of forecasting models for wind and solar energy by using the unsupervised learning machines.

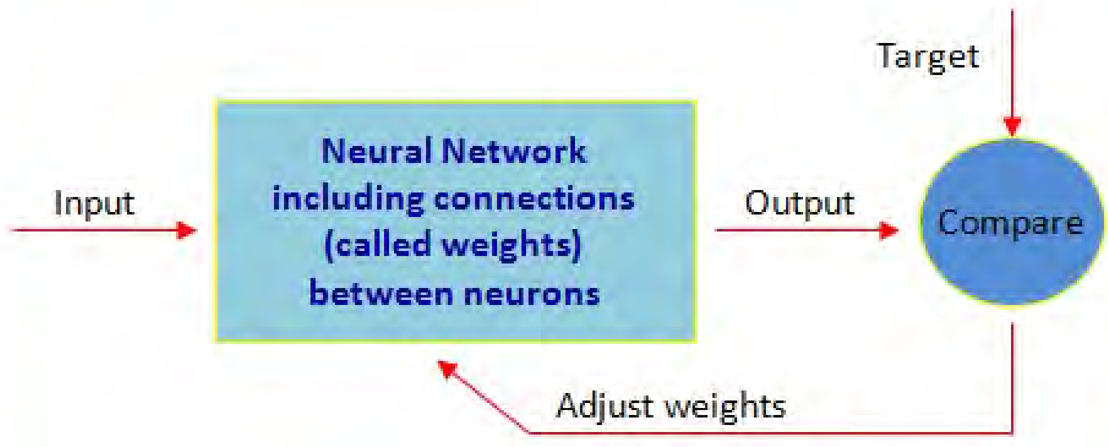
- **Artificial Neural Network (ANN)**
- **Group Method of Data Handling network (GMDH)**
- **Least Squares Support Vector Machine (LS-SVM)**

Renewable Energy Forecasting for a Microgrid



TRADITIONAL FORECASTING METHODS

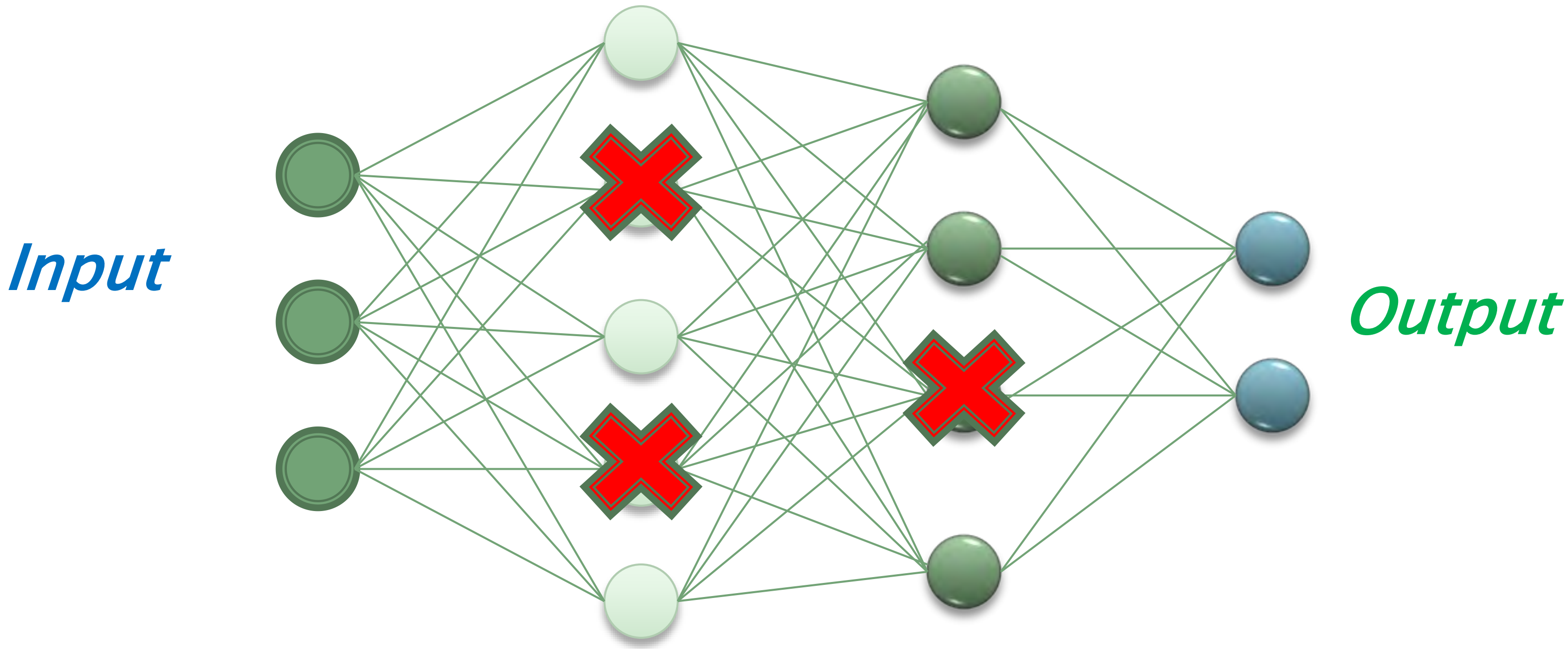
Artificial Neural Network simulates a portion of the nervous system, where the inputs are modified by weights, summed and applied a particular function. So the output signals are the sum of the weighted input signals. A particular function adjusts continuously the weights to obtain the defined accuracy of the training test



Renewable Energy Forecasting for a Microgrid

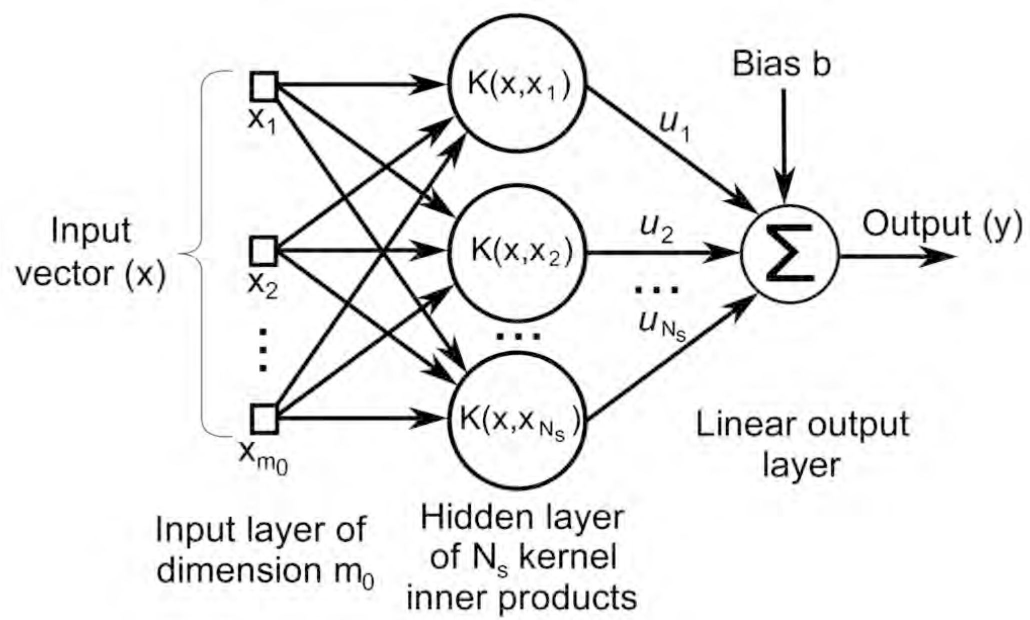
NOVEL FORECASTING METHODS

GMDH is a self organizing neural networks. This means that the connections between neurons in the network are not fixed but are selected during training to optimize the network.



NOVEL FORECASTING METHODS

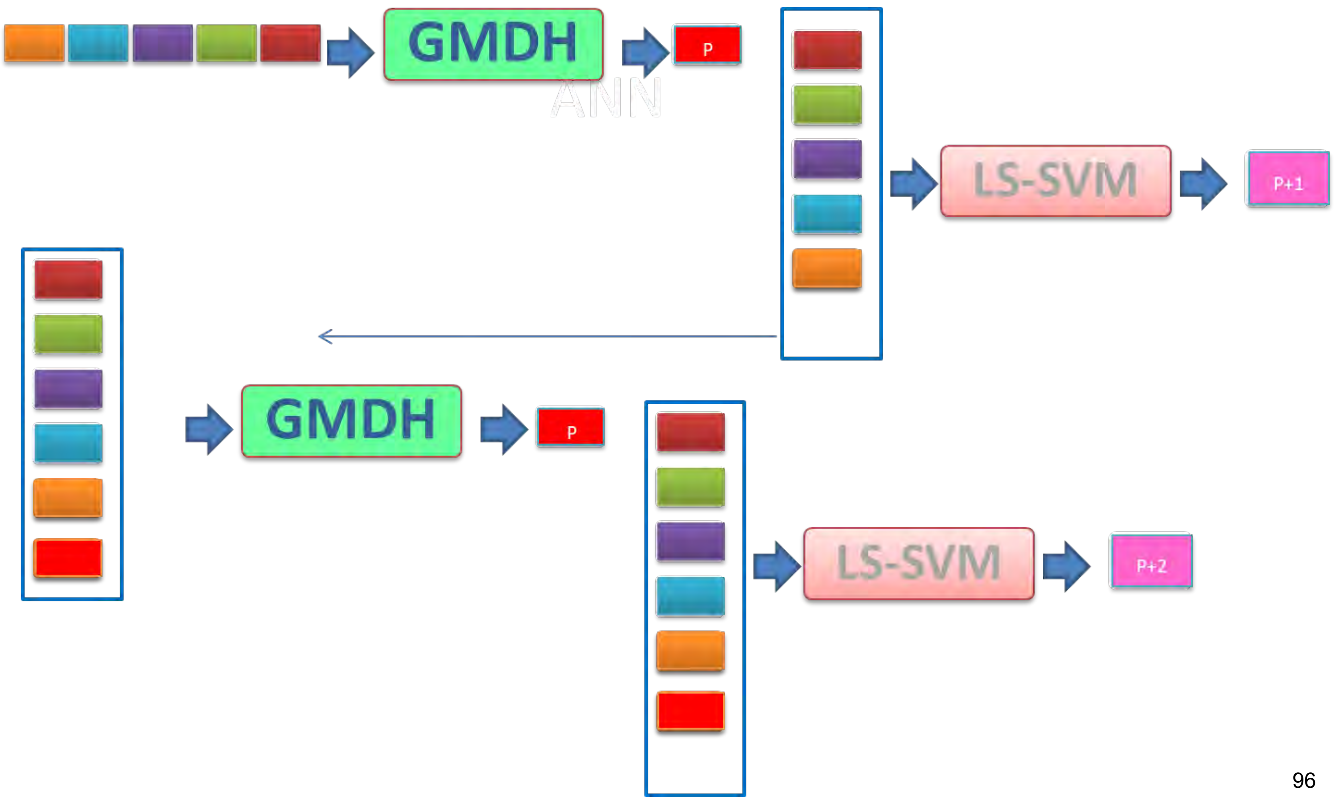
The LS-SVM is a machine learning for the solving nonlinear problems. The output is a linear combination of the kernel function for each input. LS-SVM is computationally less expensive than ANN, considering that the training requires simply the solution of a set of linear equations.



NOVEL FORECASTING METHODS

- **GLSSVM** is a hybrid model, which combines GMDH and LS-SVM.

- The output data of the GMDH model, which gives the lowest error, are used, together with the input variables, as input for LS-SVM model.



Data handling techniques

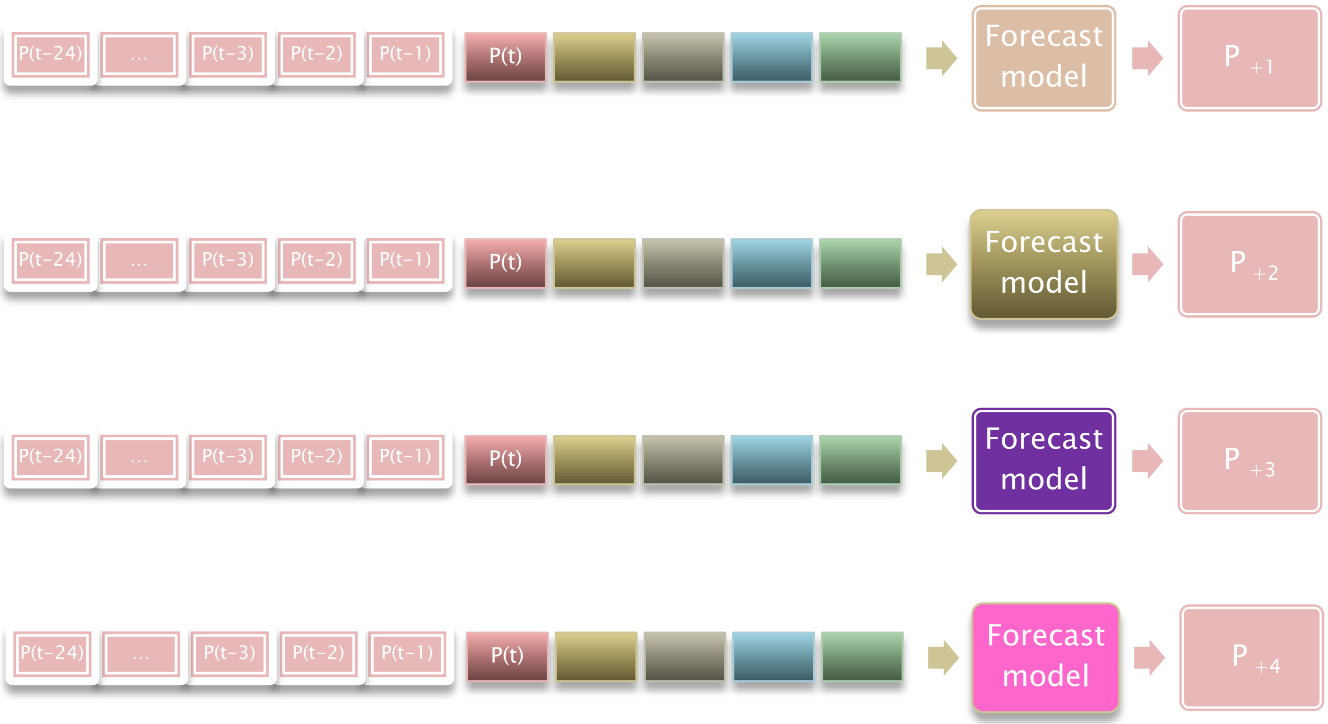
Strategies for multi-step-ahead time series forecast:

- **Direct**
- **Recursive**
- **DirRec**

Forecasting of PV Power Generation: Strategies for multi-step-ahead time series forecast

Strategies for multi-step-ahead time series forecast

Direct

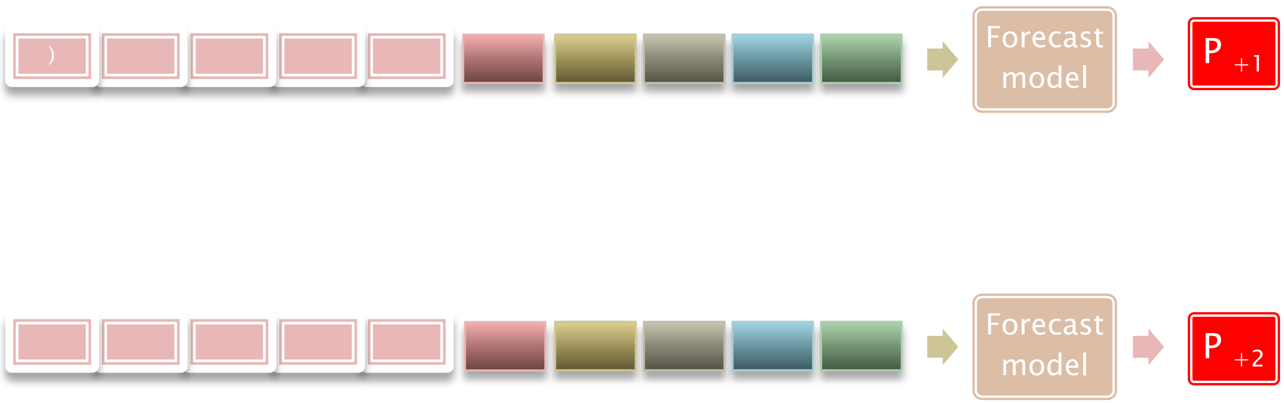


Same input vector for each horizon time

Forecasting of PV Power Generation: Strategies for multi-step-ahead time series forecast

Strategies for multi-step-ahead time series forecast

Recursive

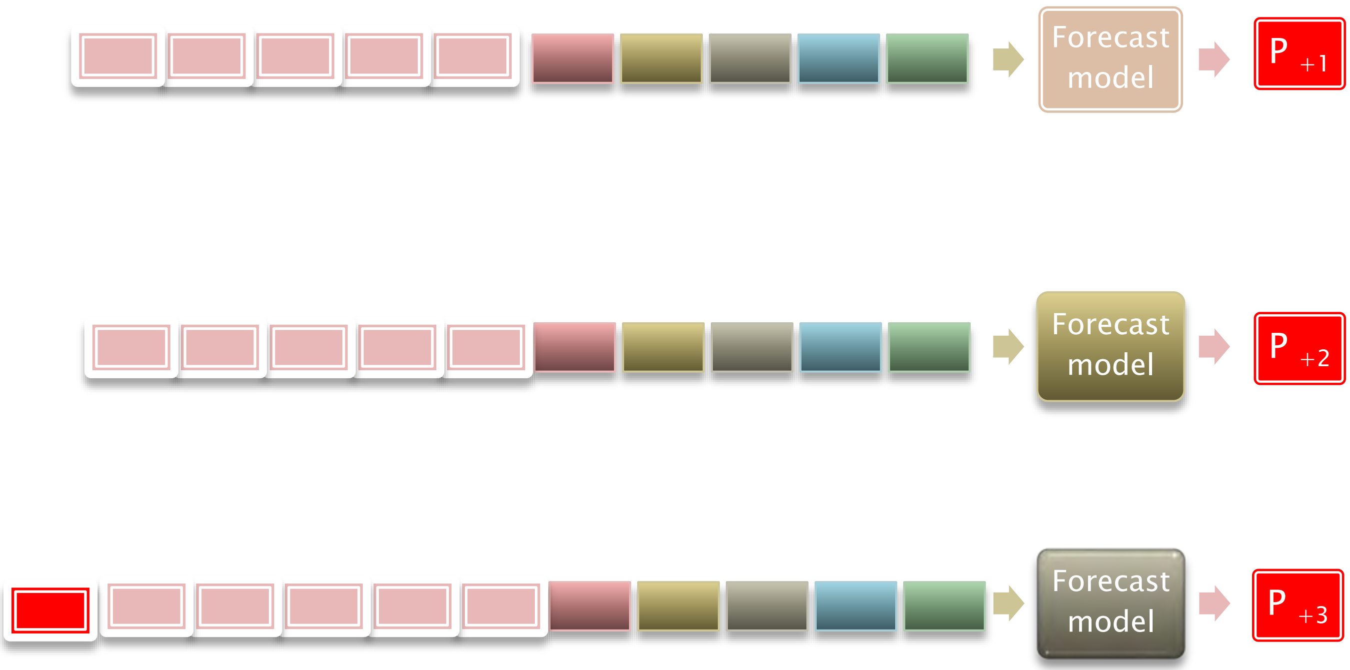


Previous predictions are used in place of the original data set as inputs to evaluate the next horizon prediction

Forecasting of PV Power Generation: Strategies for multi-step-ahead time series forecast

Strategies for multi-step-ahead time series forecast

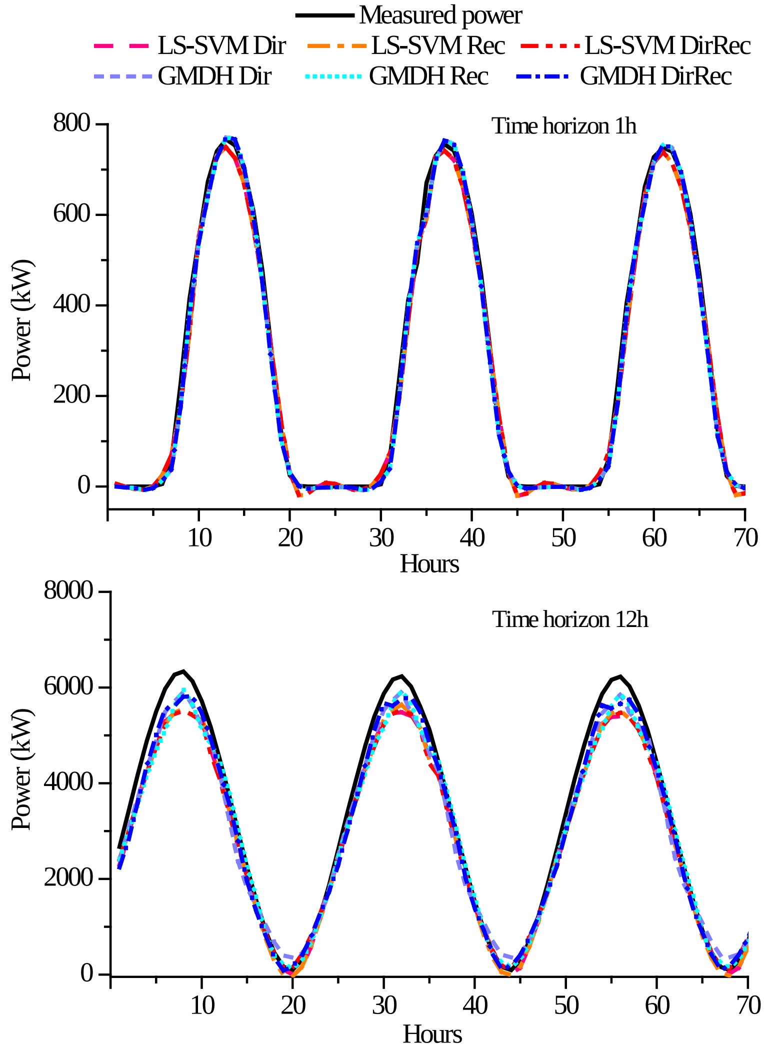
DirRec



Measured data and the previous predictions as inputs to obtain the values at the next step

Forecasting of PV Power Generation: Strategies for multi-step-ahead time series forecast

Application of the multi-step-ahead forecast strategies for LS-SVM and GMDH



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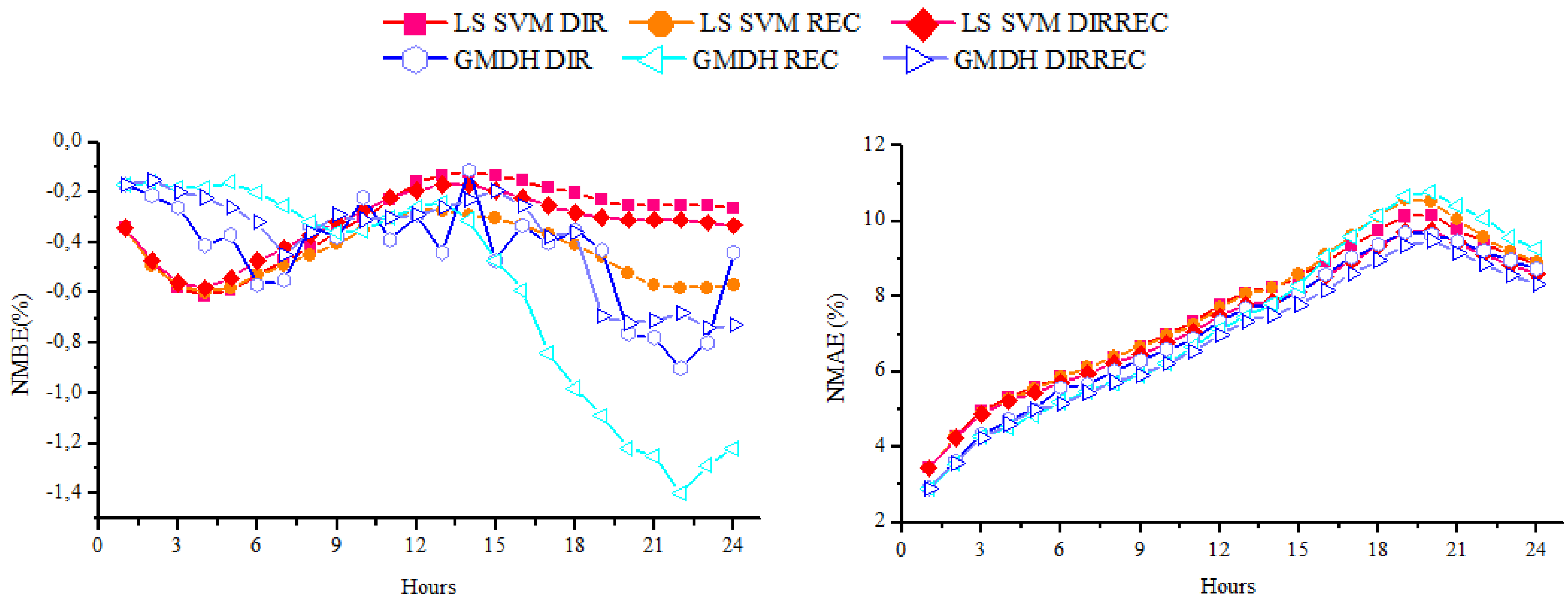

De Giorgi, M.G., Malvoni, M., Congedo, P.M. Comparison of strategies for multi-step ahead photovoltaic power forecasting models based on hybrid group method of data handling networks and least square support vector machine (2016) Energy, 107, pp. 360-373.

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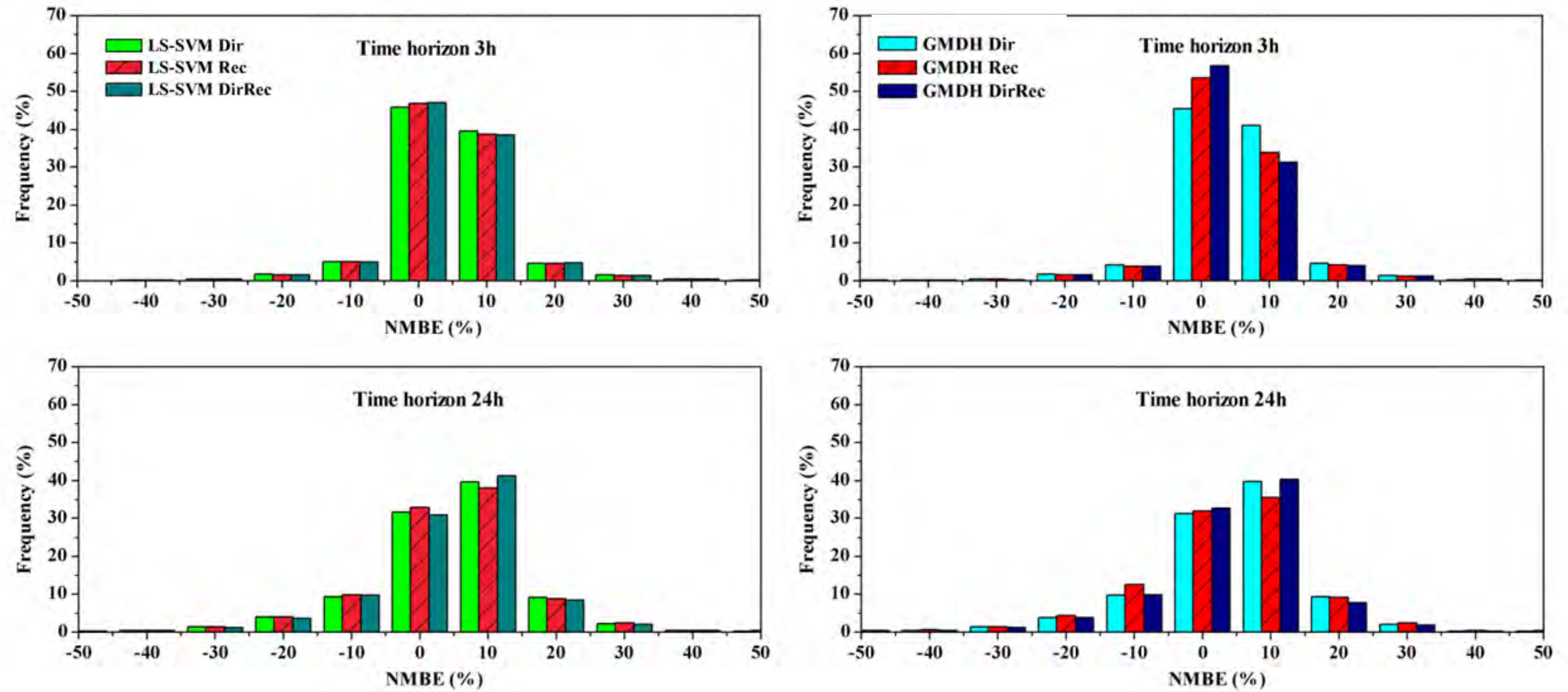

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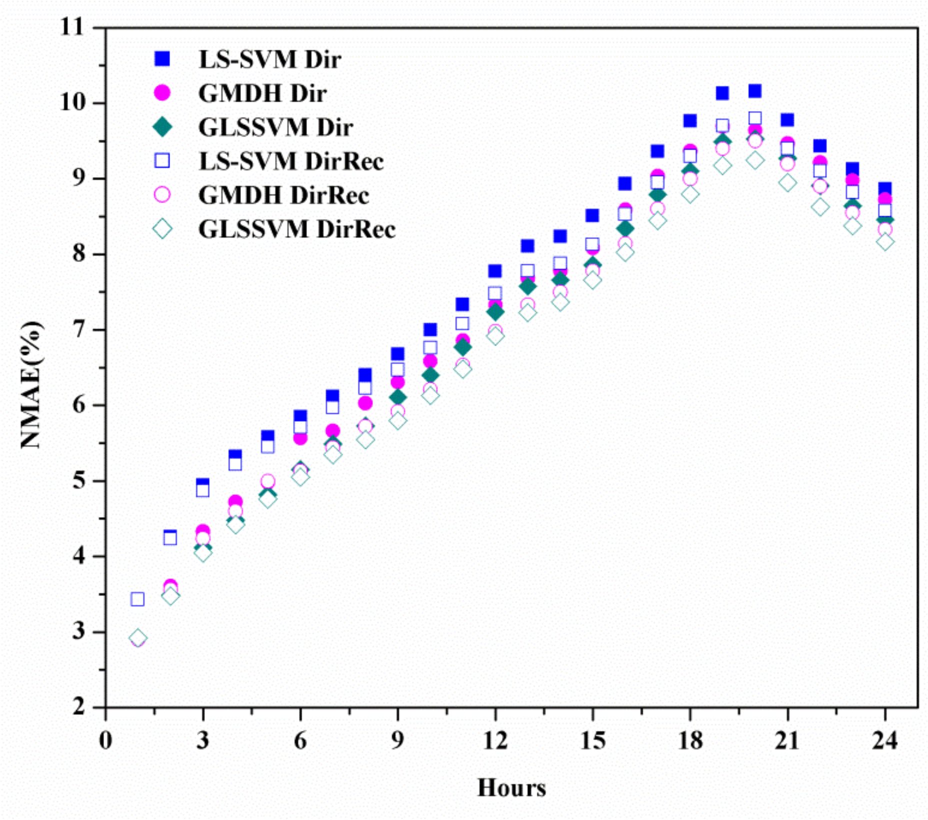

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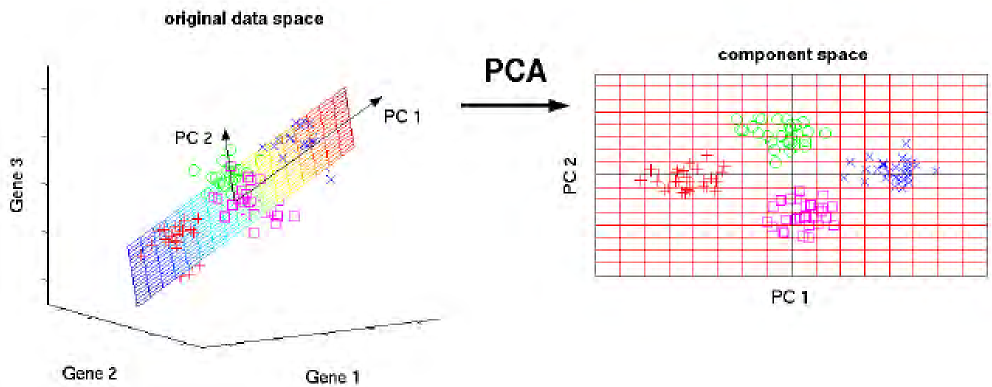
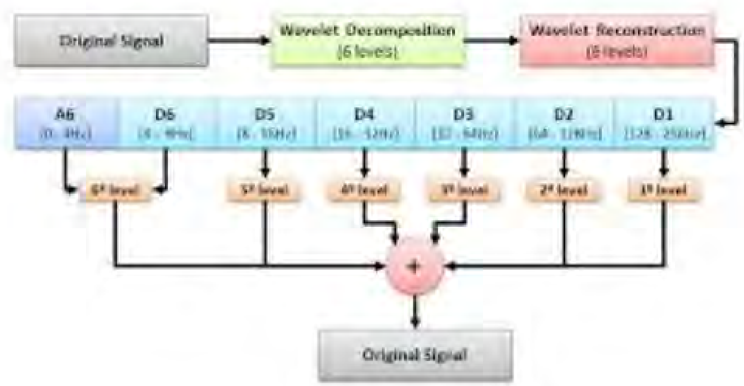
Forecasting of PV Power Generation using weather input data-preprocessing techniques

The weather parameters are the main input data to forecast the output power of a grid-connected PV system and they have a significant impact on the accuracy of the forecasting systems. Using actual measurements, it needs to deal with a huge amount of data.

The **data pre-processing techniques** represent an effective solution when the data-driven methods, based on historical measurements , are applied for the PV power generation forecasting

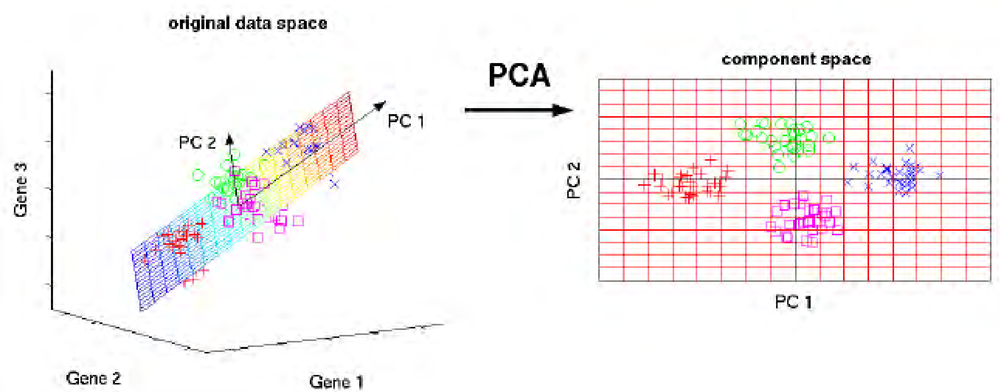
PCA and WD for data-preprocessing techniques

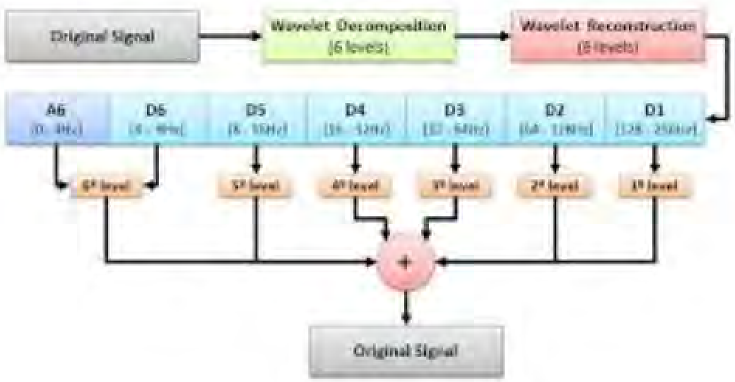




The principal component analysis (PCA) is one of the most popular techniques to remove such redundancy.

PCA and WD for data-preprocessing techniques



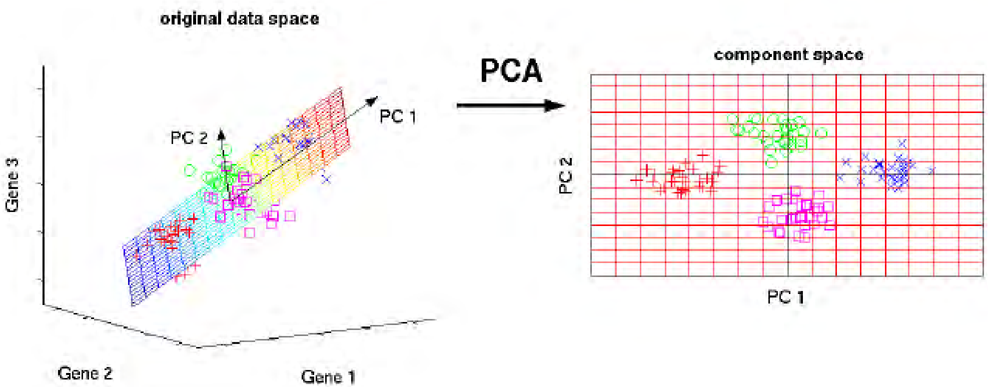


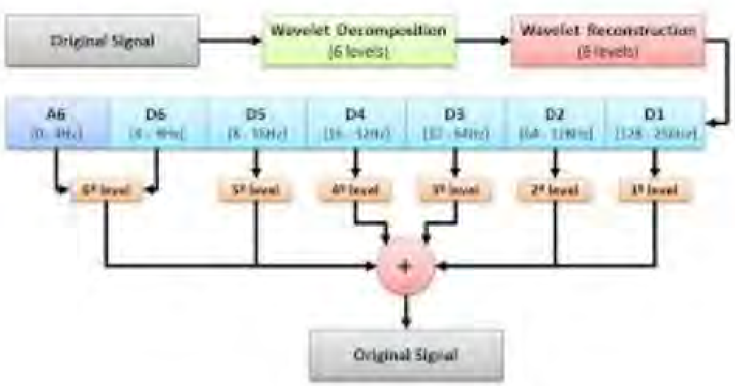
Forecasting of PV Power Generation using weather input data-preprocessing techniques

The weather variables are stochastic and introduce random fluctuations in the predicted PV power when they are used as input data in the forecast systems.

The **wavelet technique** represents an efficient solution to *reduce the noise in input datasets* before to implement a prediction model.
The wavelet decomposition (WD) applied to the input data of a forecasting model allows to deal with the *solar irradiance fluctuations*, leading to the accuracy improvement

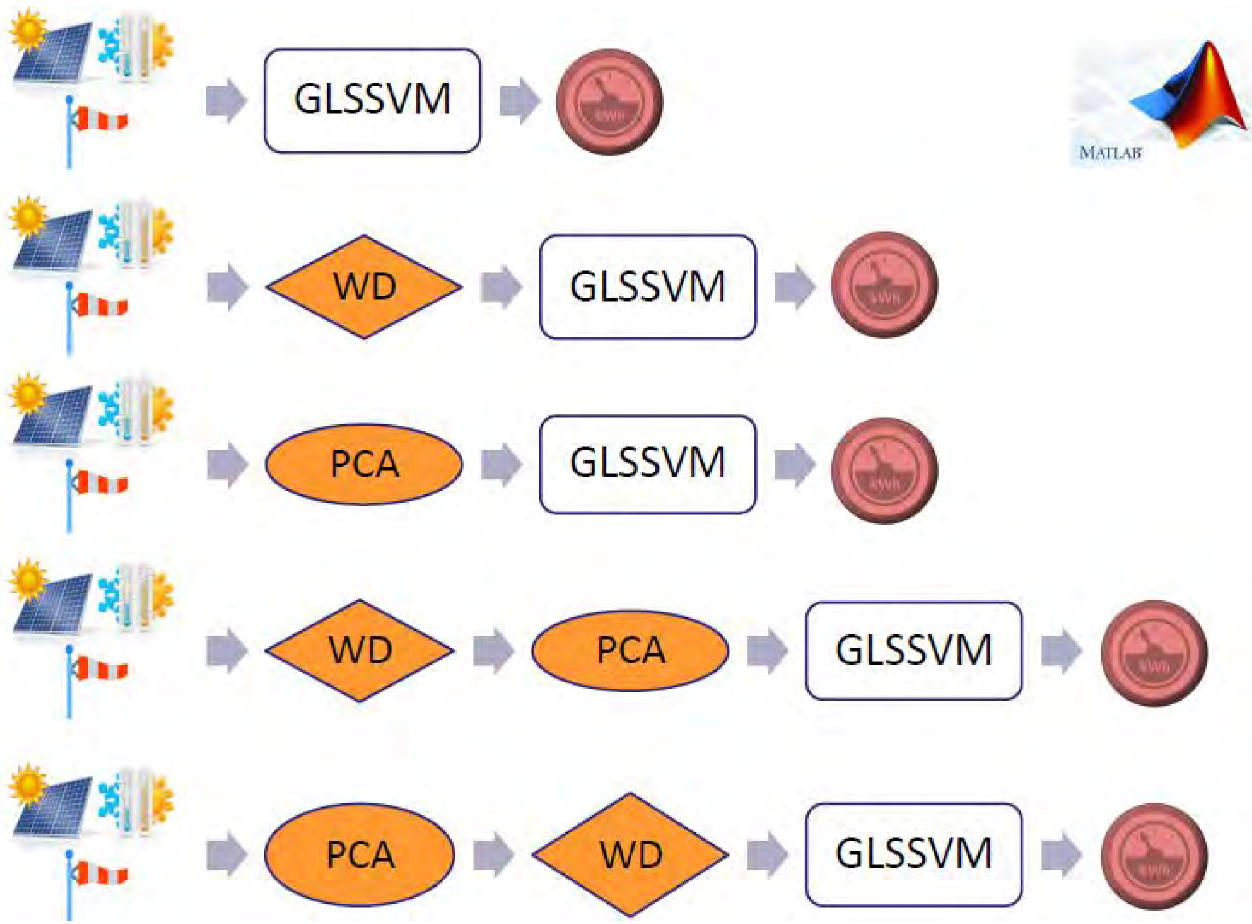
PCA and WD for data-preprocessing techniques





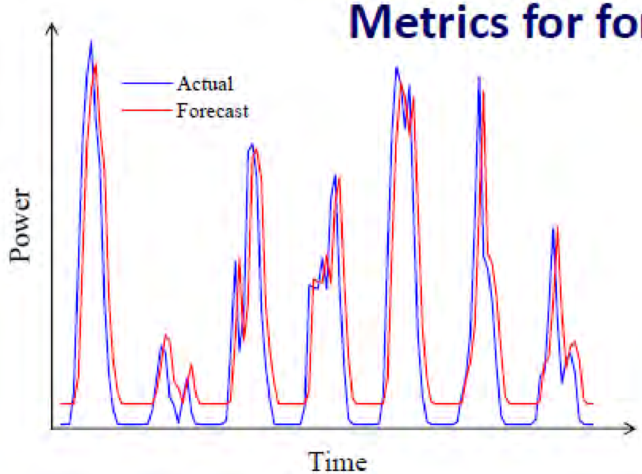
Forecasting of PV Power Generation using weather input data-preprocessing techniques

GLLSVM for the data-driven forecasting model
to predict the PV output from 1 hour to 24 hours ahead in five different approaches



Forecasting of PV Power Generation using weather input data-preprocessing techniques

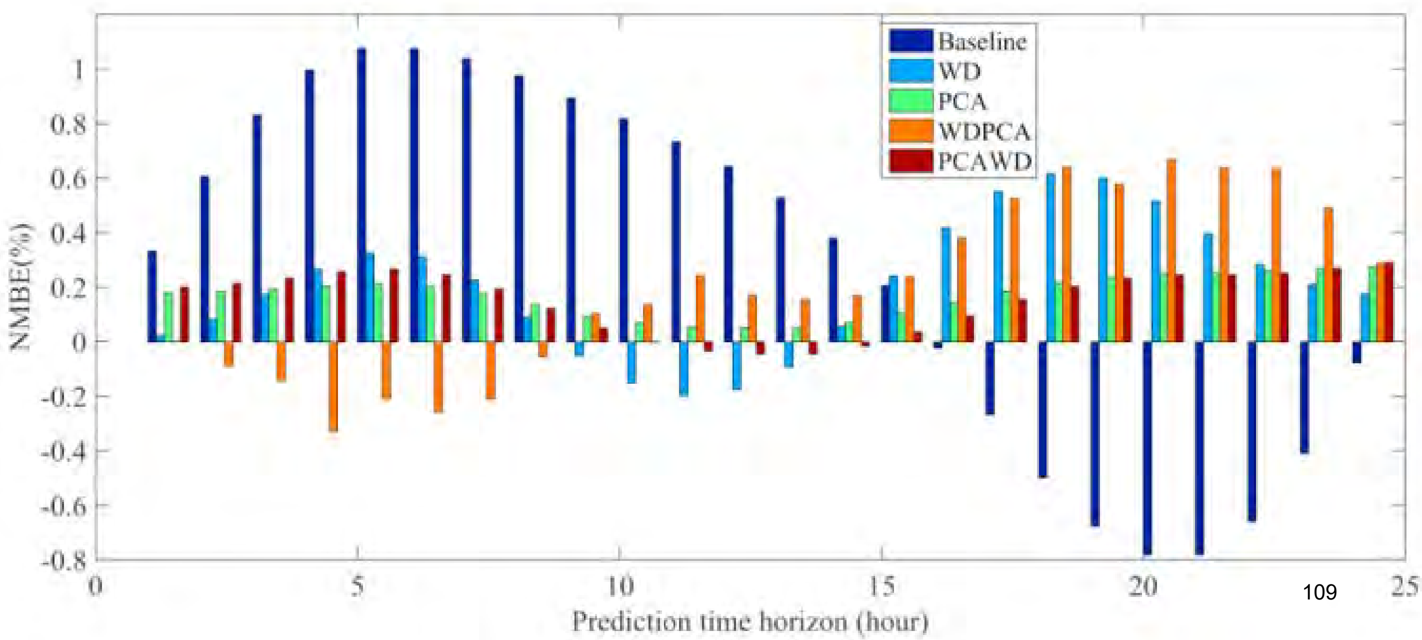
Metrics for forecast accuracy



$$E(i) = \frac{P^m(i) - P^p(i)}{Max_1^M(P^m(i))}$$

$$NMBE = \frac{1}{M} \cdot \sum_1^M E(i)$$

$$NRMSE = \sqrt{\frac{1}{M} \cdot \sum_1^M (E(i))^2}$$



Forecasting of PV Power Generation using weather input data-preprocessing techniques

The data-driven forecast method combined with the data pre-processing techniques can improve the forecast accuracy.

The PCAWD outperforms the PCA, WD and WDPCA investigated techniques in most of the hour-ahead horizons.

The wavelet decomposition of the principal components of input data can be applied to generate new input data set for the time series forecast models, allowing higher forecast performance with a decreasing of **mean error bias up to 1%**.

What is the Future in Direct Conversion Solar Energy?

From the beginning

In the 1960's W.C. Brown pioneered the field of wireless power transmission with his work on microwave rectennae. He successfully developed a helicopter powered by a microwave rectenna. The rectenna demonstrated efficiencies from 85-91%.

In 2002 ITN Energy Systems published its work on optical rectenna. The design consisted of an antenna array and a high frequency metal-insulator-metal diode to rectify the AC field across the antenna to DC power. ITN cited a range of theoretical coupling efficiencies of 85-100%

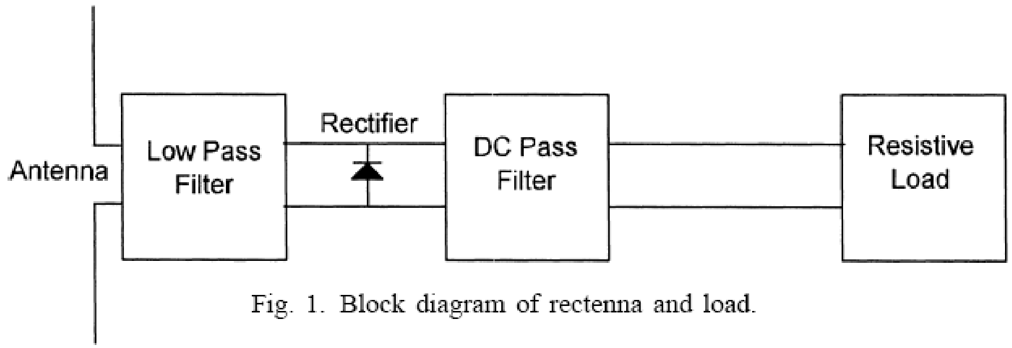


Fig. 1. Block diagram of rectenna and load.

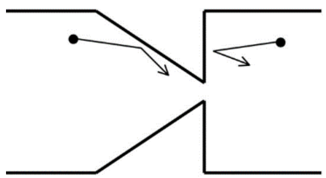
What is the Future in Direct Conversion Solar Energy?

In principle, the conversion efficiency for rectenna solar cells can be very high > 93%.

There are technical challenges on diodes and antennas:

Diodes:

- must operate efficiently at extremely high frequencies – close to a petahertz (10^{15}Hz) for visible light – i.e. orders of magnitude higher than the fastest electronics.
- must couple electrical power efficiently from the antenna. To do so, the impedance of the diode must match the low impedance of the antenna.
- One possible solution is to use geometric diodes



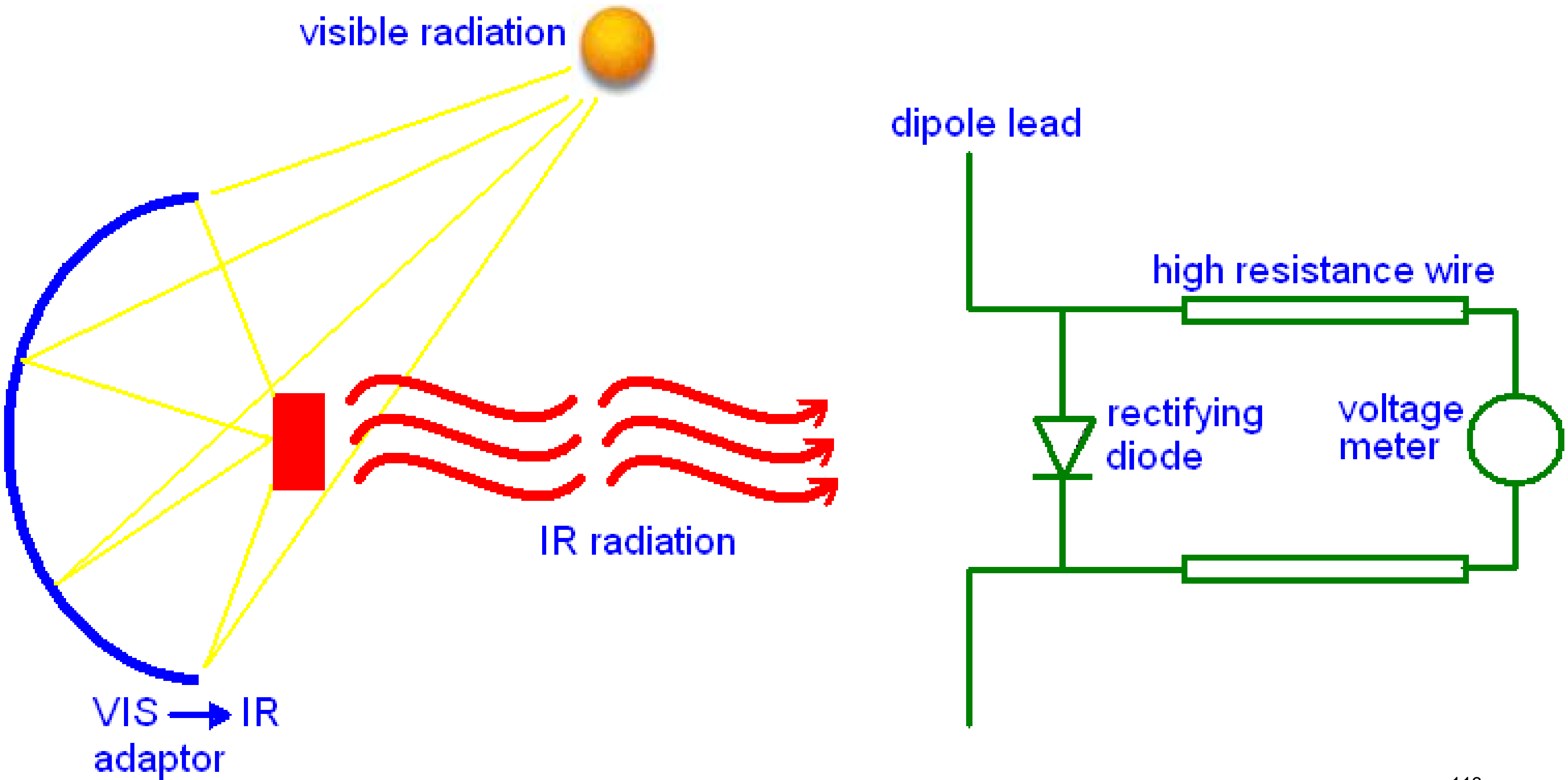
Antennas:

- power loss in the antenna, because, at petahertz frequencies, metals become very resistive. One possible solution is to use dielectric antennas.

?

The principle has been proven to work in the microwaves and IR region, but is it still working with visible light?

The First Experimental Setup



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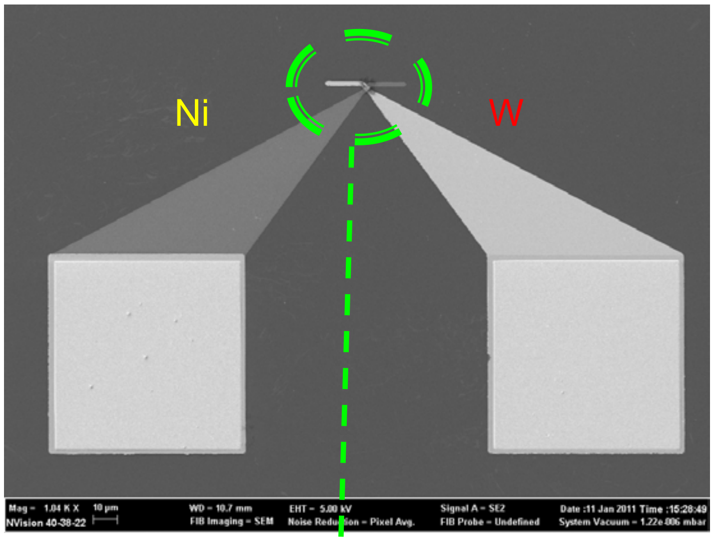
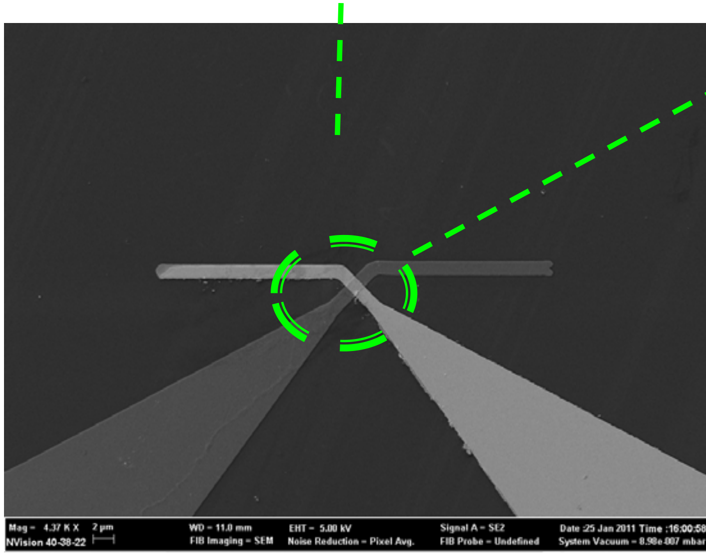
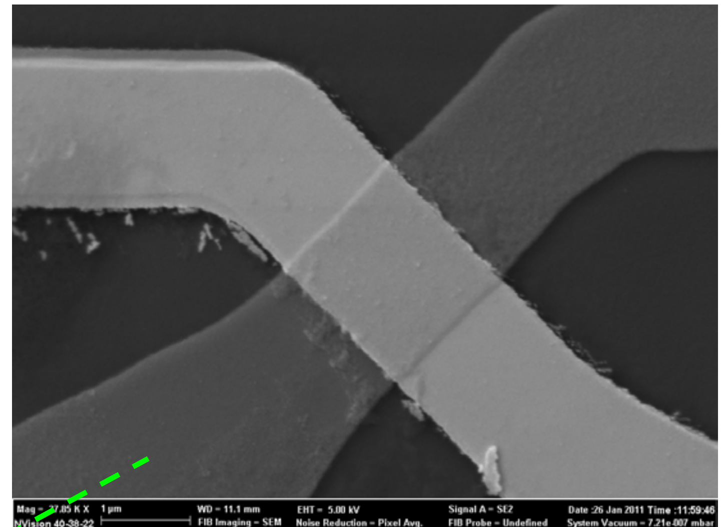
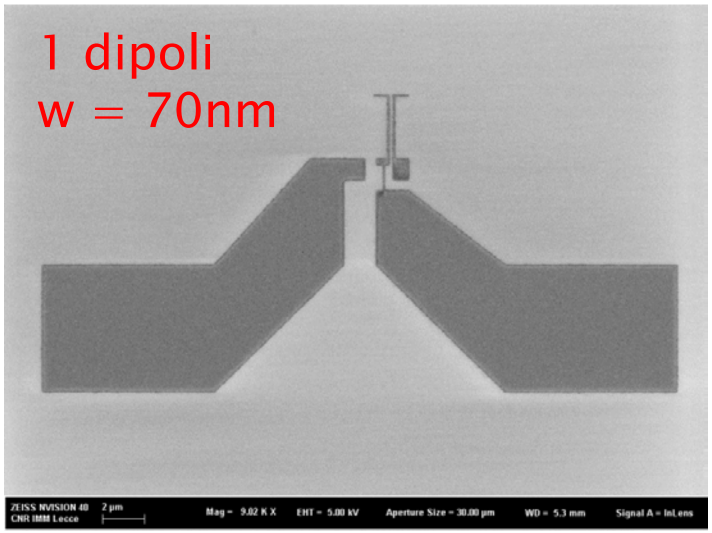


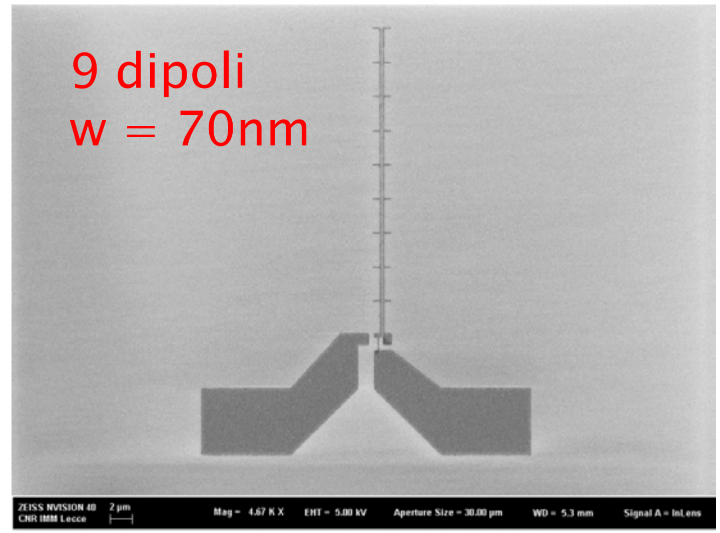


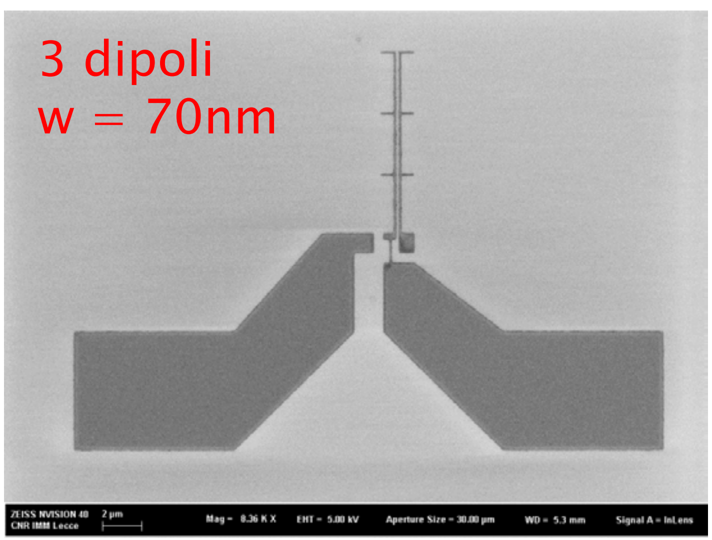


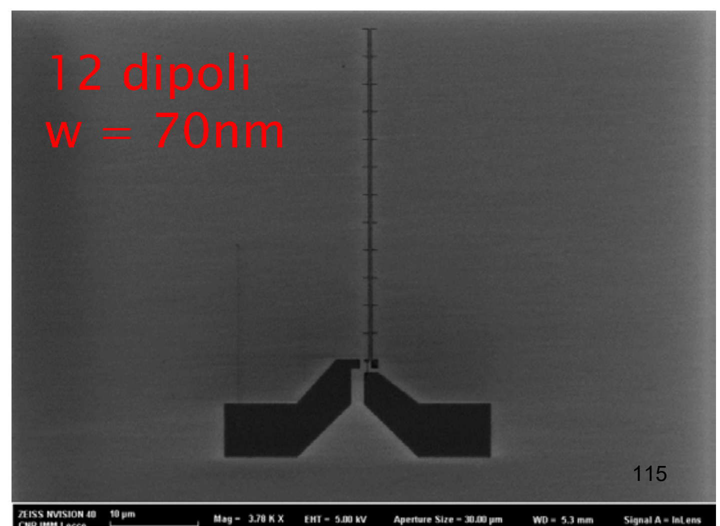
- W (40nm) / WO_x / Ni (15nm)
- Plasma Oxidation via O_2
- MIM Area 1.5 x 1.5 μm^2
- Dipole L = 2 x 18 µm

The First Prototypes



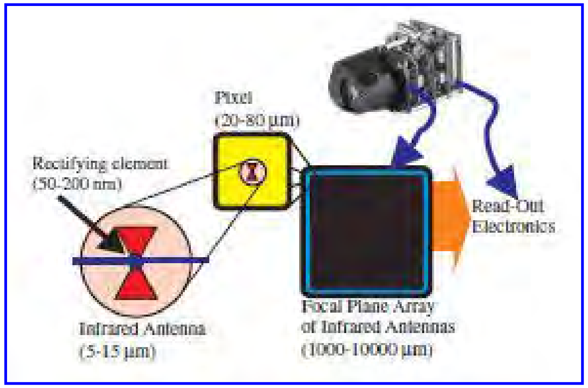


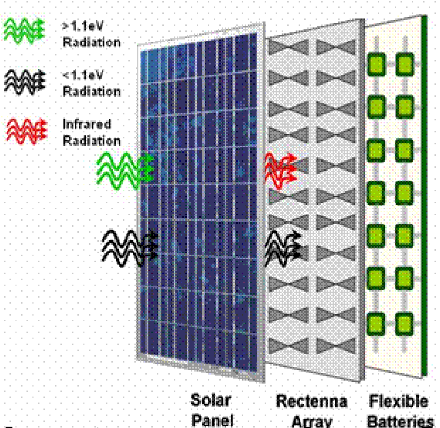




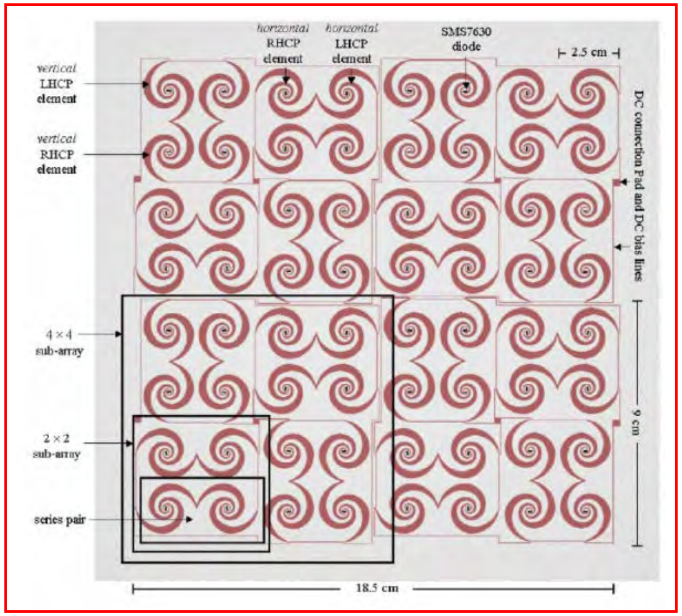
Possible Side-Technology Applications

Detectors for IR/THz Imaging sensors





Direct conversion of Solar Energy and lighting / heating systems



- **RF Energy harvesting (2-18 GHz)** – to power portable devices