



Machine Learning Model Selection for PV Forecasting

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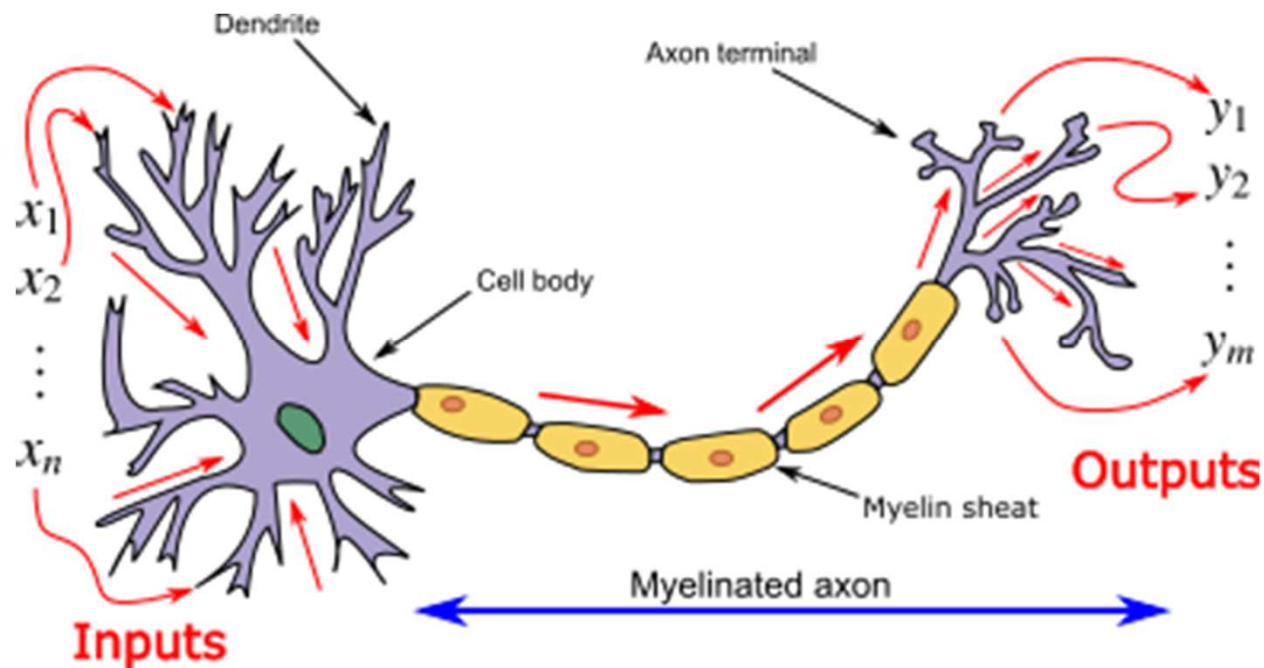


Outline

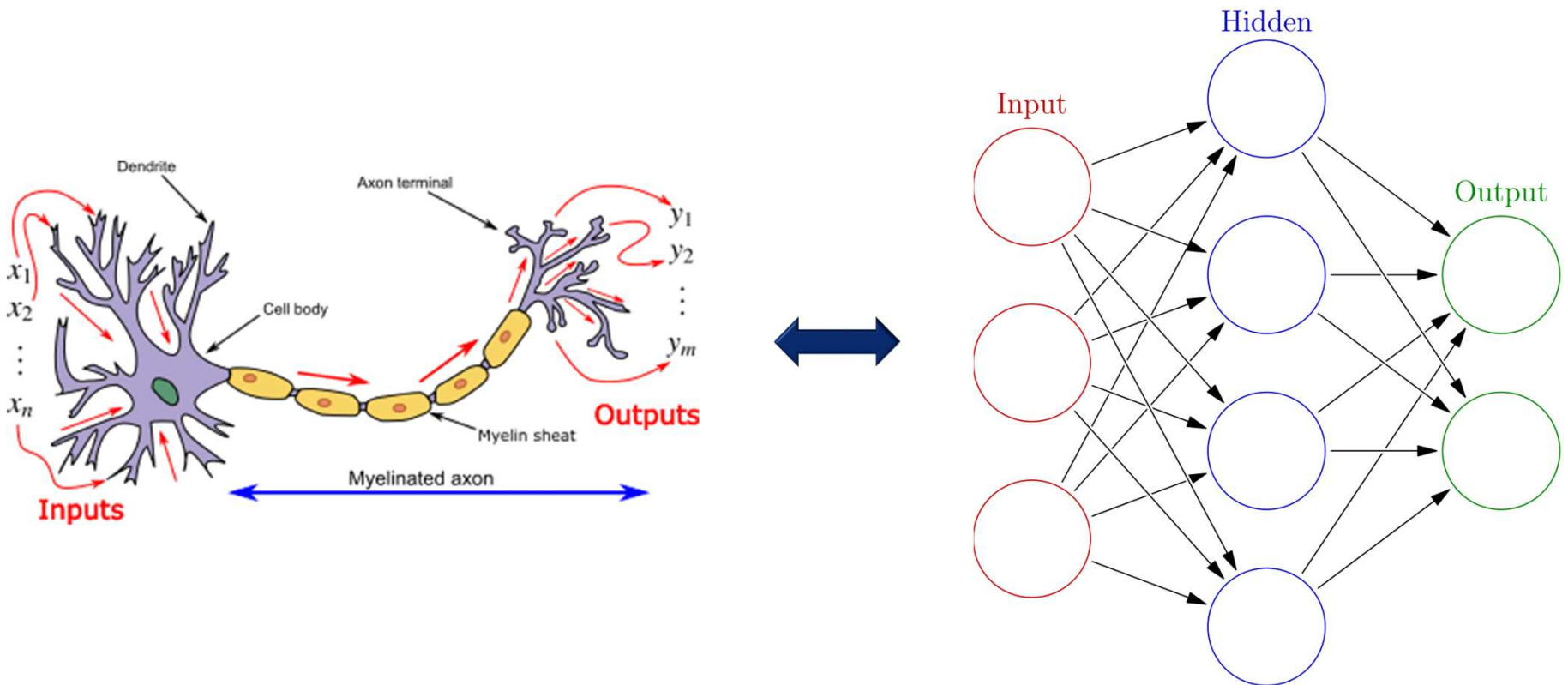
- Artificial Neural Networks
- Support Vector Machines
- Trees
- Model Selection
- Methodology
- Results



Artificial Neural Networks

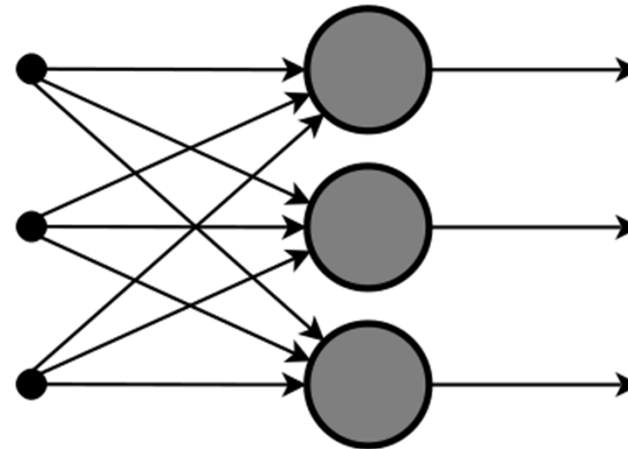


Artificial Neural Networks



Artificial Neural Networks

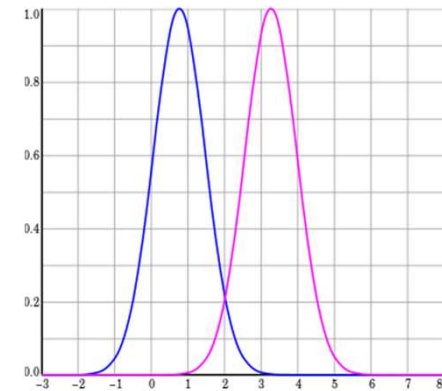
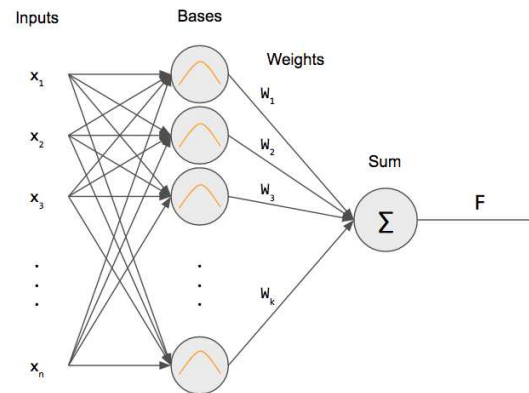
- Types of ANN:
 - Feedforward Neural Network



- Applications:
 - Computer Vision (Sky and Satellite Images for intra-day forecasts)
 - Speech Recognition

Artificial Neural Networks

- Types of ANN:
 - Radial basis function Neural Network

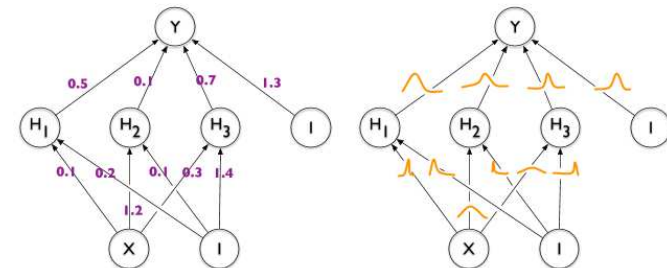


- Applications:
 - Power Restoration Systems

Artificial Neural Networks

- Types of ANN:
 - Bayesian Neural Networks

$$p(w|y) = \frac{p(y|w)p(w)}{p(y)} \quad p(w) = N(w|0, \sigma_p^2 I_D)$$



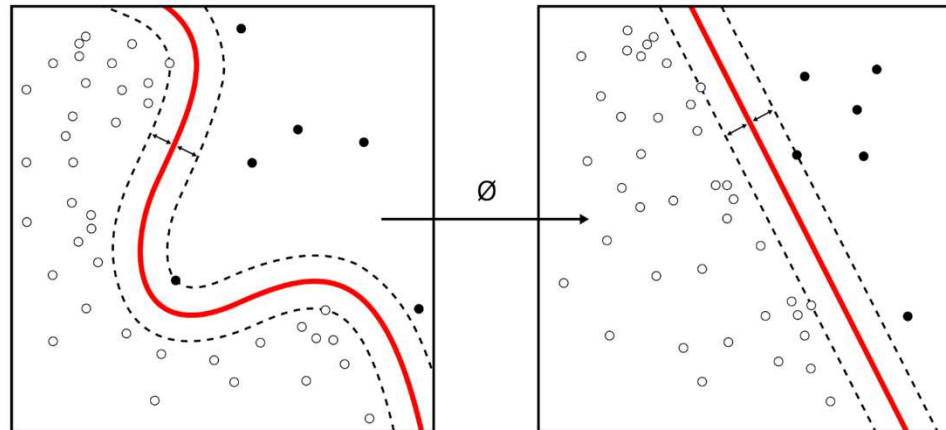
- Applications:
 - Variety of areas

Artificial Neural Networks

- Types of ANN:
 - Feedforward Neural Network
 - Radial Basis Function Neural Network
 - Bayesian Neural Network
1. Weight optimization
 2. Programmable
 3. Fast

Support Vector Machines

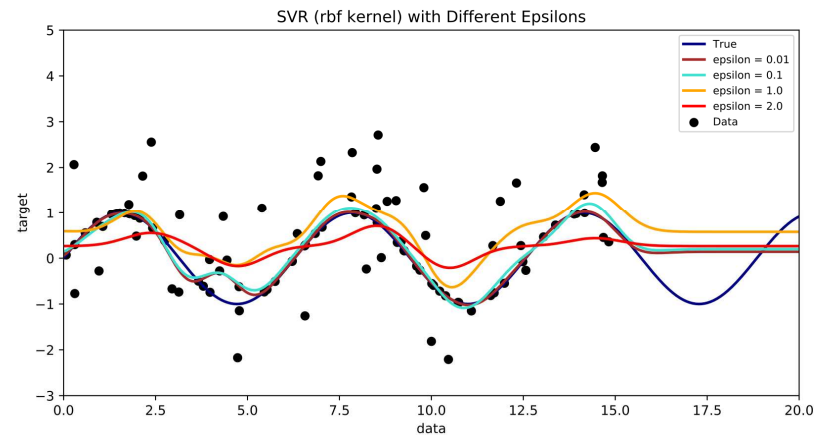
- Support Vector Machines for Classification



- Applications:
 - 2 class classification
 - Multiclass SVM: Not accurate

Support Vector Machines

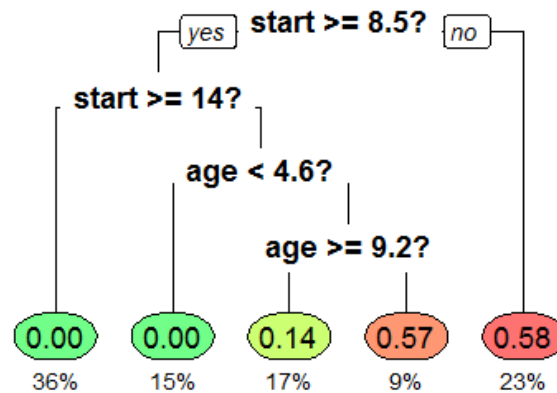
- Support Vector Machines for Regression



- Applications:
 - Simple Regression Problems (e.g. intra-day forecasting)

Trees

- Decision Trees



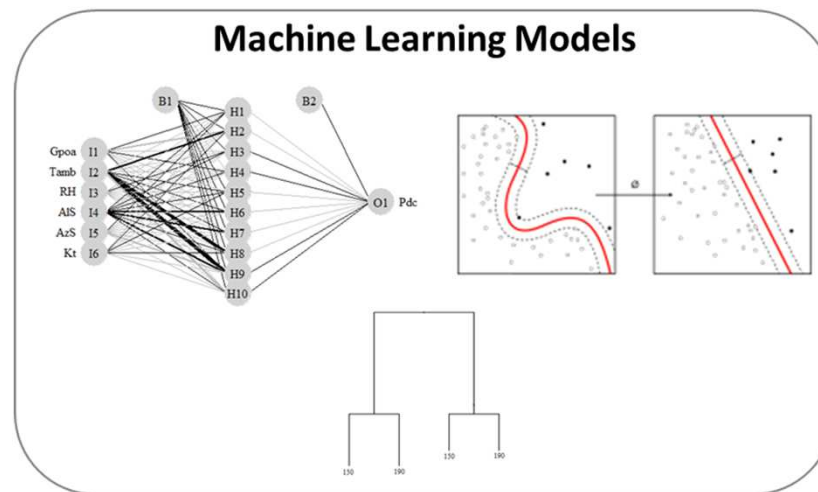
Trees

- Classification and Regression Trees (CART)

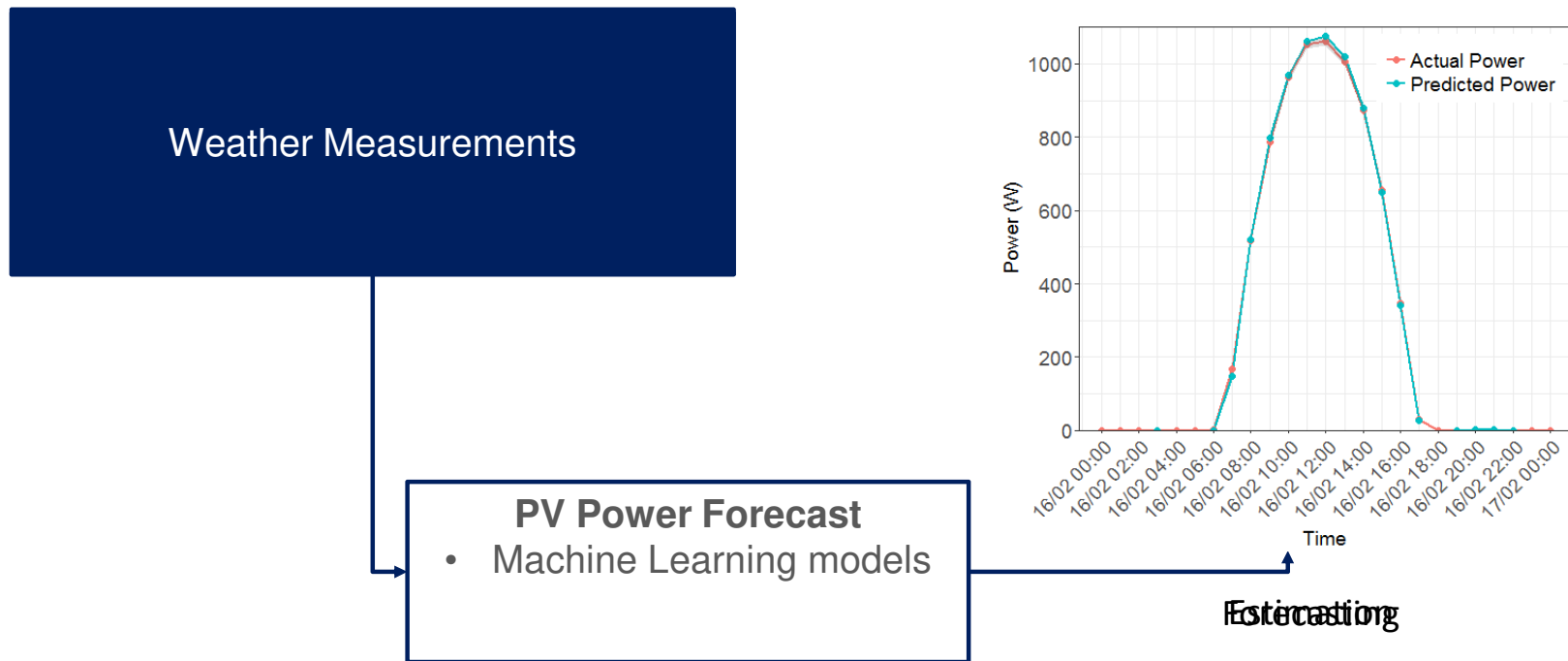


Model Selection

- Bayesian Neural Network
- Support Vector Machine for Regression
- Regression Trees

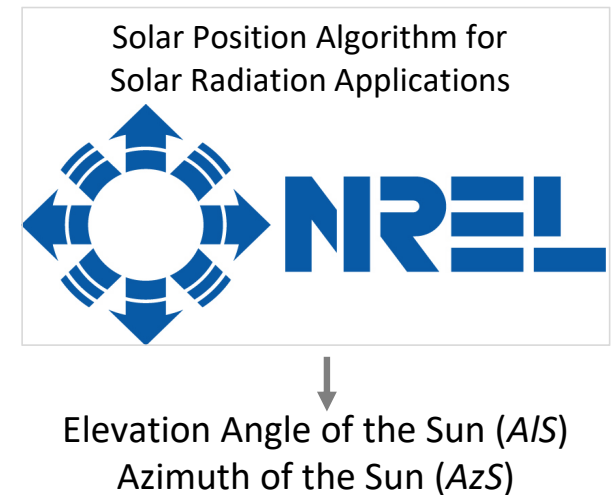


Model Selection



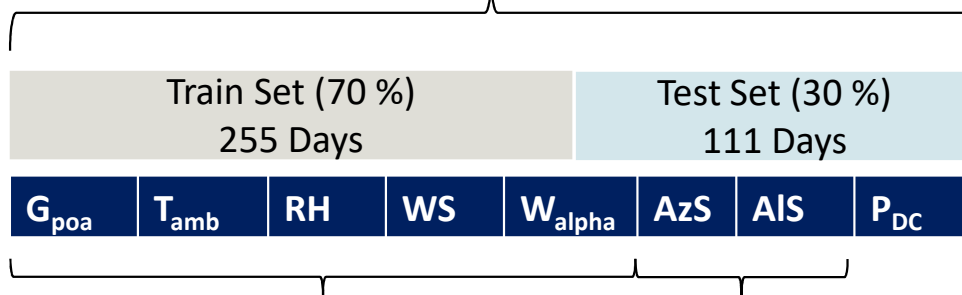
Methodology – Experimental Apparatus

- Grid-connected Poly-c-Si PV (1.3 kWp).
- Monitoring system to acquire PV operational and meteorological measurements.
- Data acquired since June 2015 and accumulated as 60-minute averages.



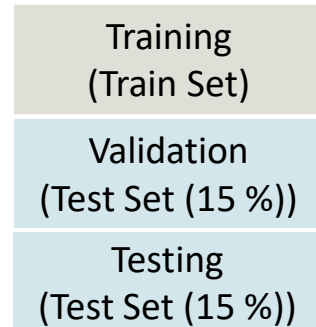
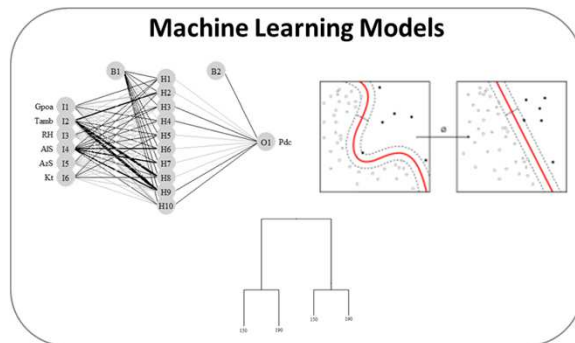
Methodology-Machine Learning Approach

Data set (1 year of hourly data)



Measured

Calculated



1. Data preparation

- Data split (Representative)
- Feature extraction
- Outlier correction

2. Models Design

- Optimization
- Architectural Design
- Validation

Methodology-Assessment Metrics - Validation

$$MAE = \frac{1}{n} \times \sum_{i=1}^n |y_{\text{actual},i} - y_{\text{predicted},i}|$$

$$MAPE = \frac{100}{n} \times \sum_{i=1}^n \left| \frac{y_{\text{actual},i} - y_{\text{predicted},i}}{y_{\text{actual},i}} \right|$$

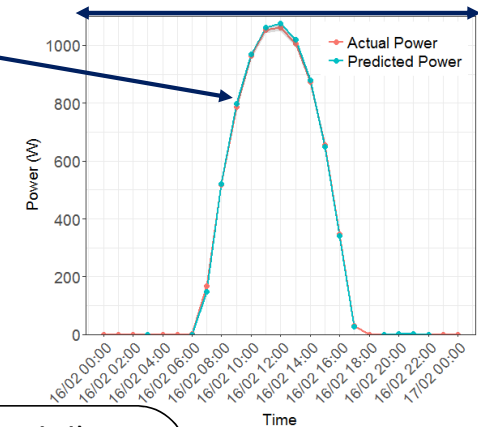
$$RMSE = \sqrt{\frac{1}{n} \times \sum_{i=1}^n (y_{\text{actual},i} - y_{\text{predicted},i})^2}$$

$$nRMSE = \frac{100}{P_{\text{nominal}}} \times \sqrt{\frac{1}{n} \times \sum_{i=1}^n (y_{\text{actual},i} - y_{\text{predicted},i})^2}$$

$$SS = 100 \times \left(1 - \frac{RMSE_{\text{predicted}}}{RMSE_{\text{reference}}} \right)$$

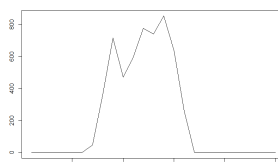
MBE / RMSE / nRMSE(%) over a day period

Error / APE for each point

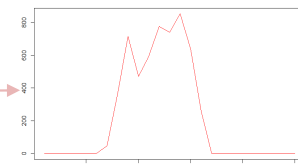


Persistence Model (Reference Model)

Measurements for Day (D)



Forecast for D + 1

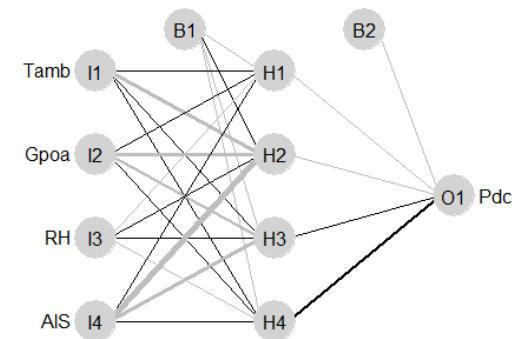


Results-Input parameters

Input Correlation Analysis (Pearson)

Cutoff $<|0.5|$

	P_{DC}
G_{poa}	0.9
AIS	0.8
RH	-0.7
T_{amb}	-0.5
W_{alpha}	-0.3
WS	0.2
AzS	-0.01
Rain	0.0005

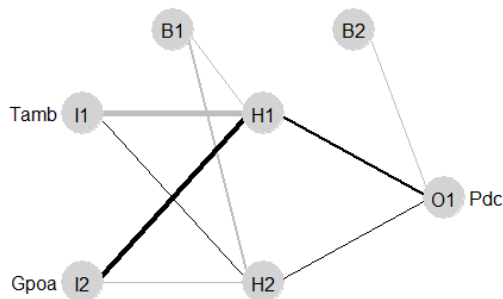


Reference Model

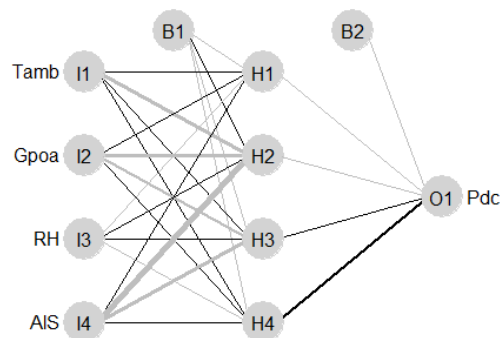
Results-Input parameters

Continuous Samples

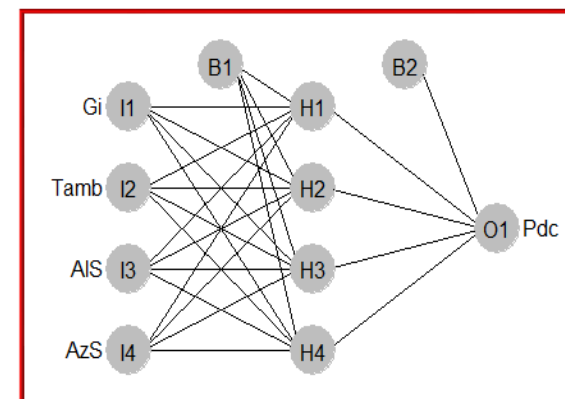
nRMSE(%) 1.15 %



nRMSE(%) 1.08 %



nRMSE(%) 0.90 %



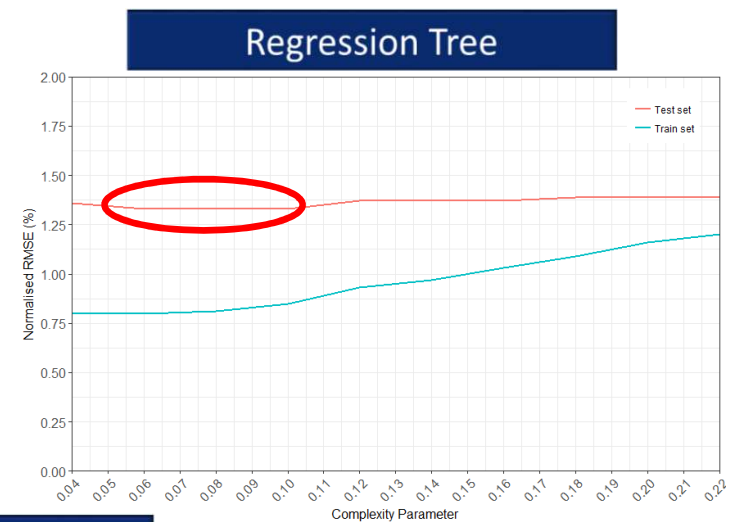
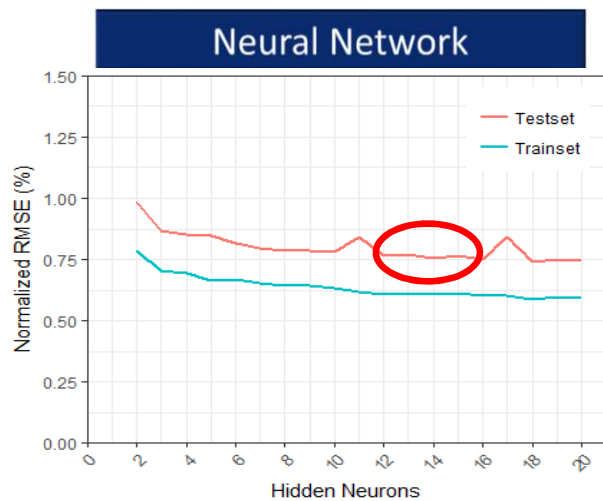
Random Samples

nRMSE(%) 1.11 %

nRMSE(%) 1.01 %

nRMSE(%) 0.80 %

Results-Architectural parameters



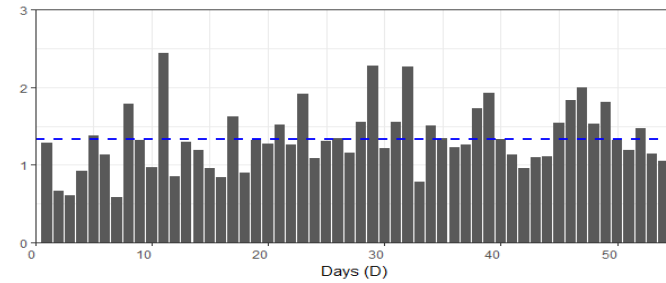
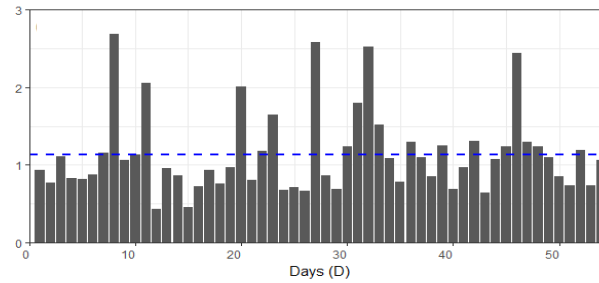
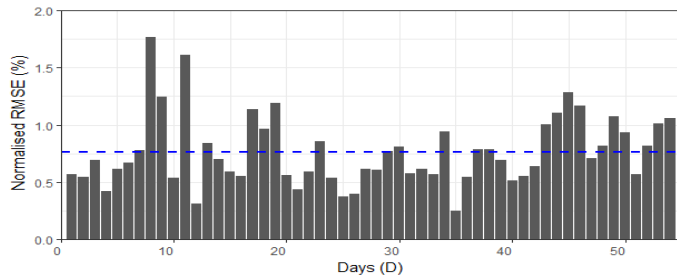
Support Vector Regression				
Gamma Parameter, γ (γ)	Cost of Constraints Parameter, C (C)			
	1	100	1000	10000
0.0001	1.1395	1.1453	1.1411	1.1388
0.001	1.1405	1.1512	1.1427	1.1762
0.01	1.1387	1.1485	1.1659	1.1793
0.1	1.1321	1.499	1.1439	1.1873

Results-Optimized Models

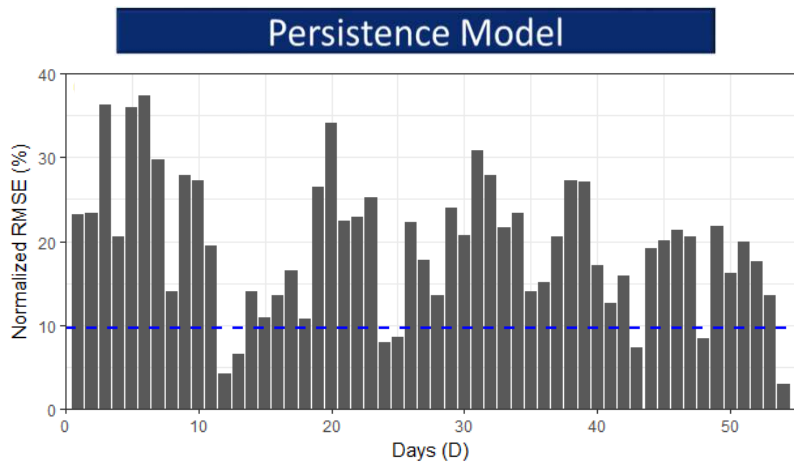
Neural Network
12 Neurons

Support Vector Regression
0.1 Gamma
1 Cost of Constraints

Regression Trees
0.06 Complexity Parameter



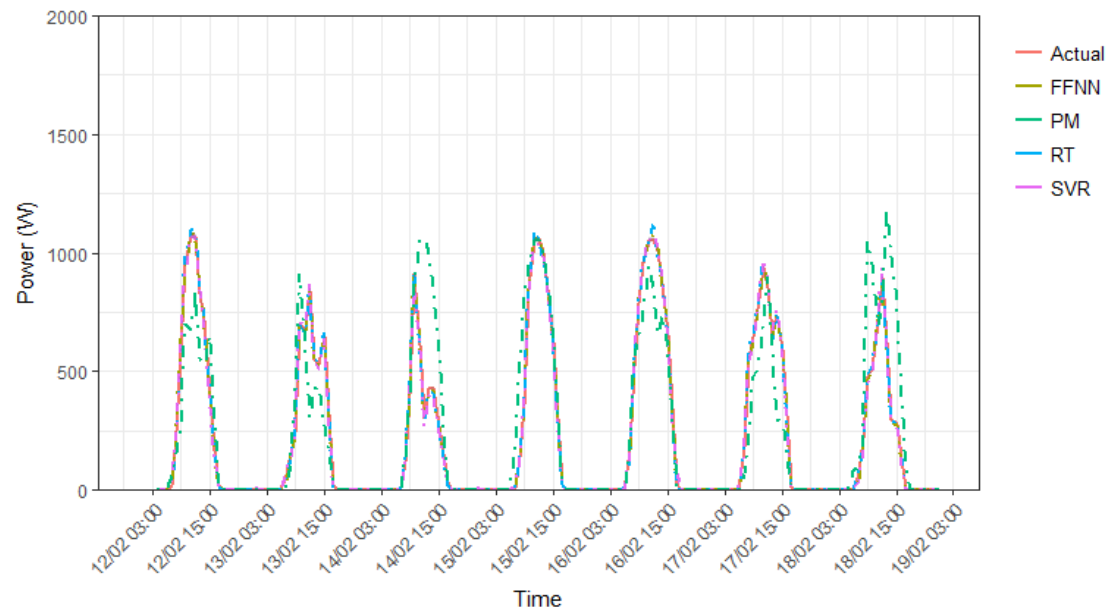
Results-Models Assessment



	Performance Metrics			
Models	MAPE (%)	RMSE (W)	nRMSE (%)	SS (%)
ANN	0.61	10.37	0.76	92.22
SVR	0.75	15.42	1.13	88.34
RT	0.98	18.15	1.33	86.33

Results-Models Assessment

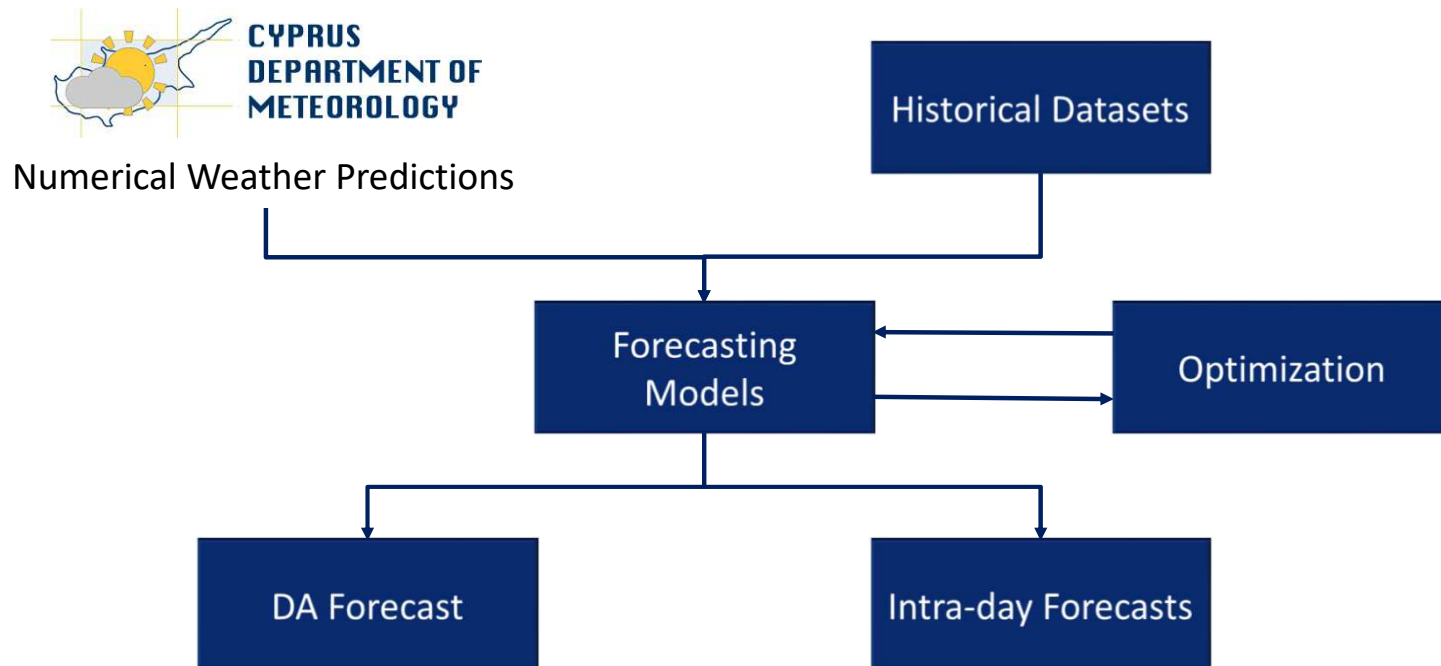
- Plot of a typical week



Conclusions

- Machine learning models could be utilized for the implementation of agile PV power forecasting techniques.
- Results demonstrated that by utilizing simple machine learning techniques (ANNs, RT and SVR), exhibits nRMSEs ~ 1 %.
- The ANN model demonstrated the best-performance over the RT and SVR with nRMSE of 0.76 % while the SVR and RT demonstrated nRMSE of 1.13 % and 1.33 % respectively.
- Finally, all the models achieved higher relative improvement over the reference model, since the SS results ranged from 86 % to 92 %.

General Methodology



More information...

Website

www.pvtechnology.ucy.ac.cy



Highlights



Mediterranean Smart Grid
Technology Platform formation.
[Read more...](#)



European award at the 29th EU-
PVSEC conference.
[Read more...](#)



Conercon - UCY strengthen their
collaboration.
[Read more...](#)

Upcoming Event



PV-NET Final Conference - 8 May 2015
[Provisional Agenda](#)

Latest News

— DERlab Presents Its Activity Report
2014/2015.

— National Technical University of Athens and
FOSS sign research collaboration agreement.

— FOSS and Alfa Mediterranean Enterprises Ltd
join forces.

— Pilot Smart Meters with DSM and PV
generation under way in Cyprus.

— Smart meters and EMF.

Thank you for your attention

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