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DIEGO

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University of Cyprus
PV Technology

Day-ahead and Intra-day PV production Forecasting

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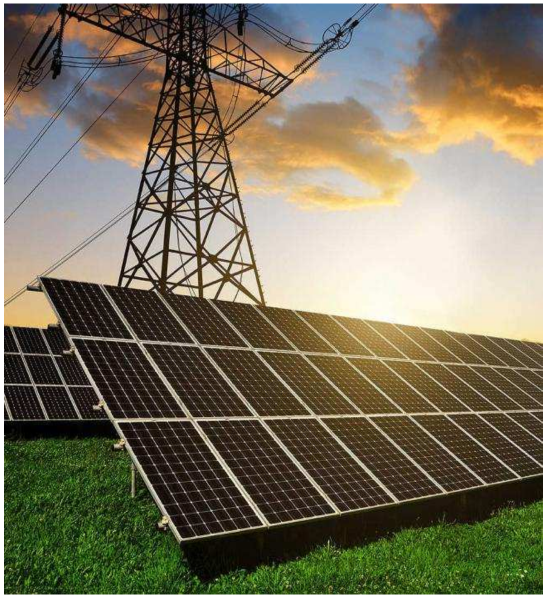
Special Scientist, University of Cyprus

Outline

- Introduction
- Approach
- Motivation
- Experimental Apparatus
- Data Quality Routines
- Day-ahead Forecasting
- Intra-day Forecasting
- Regional PV Power Forecasting
- Conclusions

Introduction

- Current focus on PV production forecasting because of the **increasing number of grid-connected PV systems** and the need for **predictable generation**.
- Important for both grid and plant operators:
    - Ensures grid stability and dispatchability of the electric system (energy management and grid flexibility).
    - Advancement of commercialization for selling onto the next day market.



Background & Objectives

- **The focus is to provide accurate Day-ahead (DA) and Intra-day PV production forecasts for point and regional sites in the state-of-the art levels.**

Specific Objectives

- Develop data-driven approaches to yield accurate forecasts only on historical data.
- Prove whether the forecasting accuracy can reach state-of-the art levels.
- Establish a DA and Intra-day PV power forecasting tool that will also act as a multi-agent system for active grid management.

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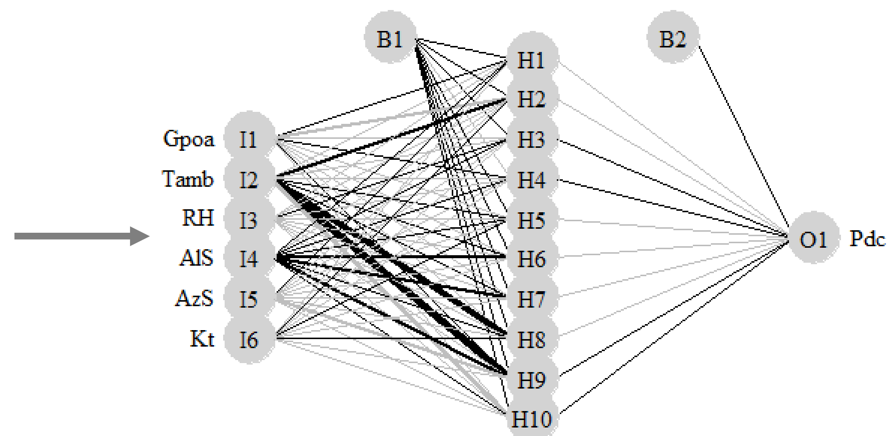
Approach

- **ANNs can approximate any linear and nonlinear mapping.**
- **PV system information not required - Capture systematic behaviour.**

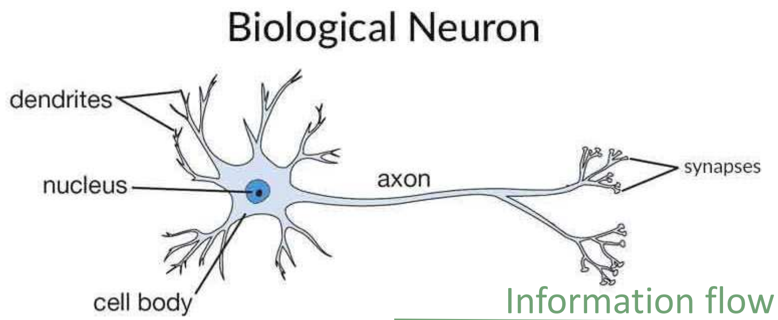
Historical Data feed

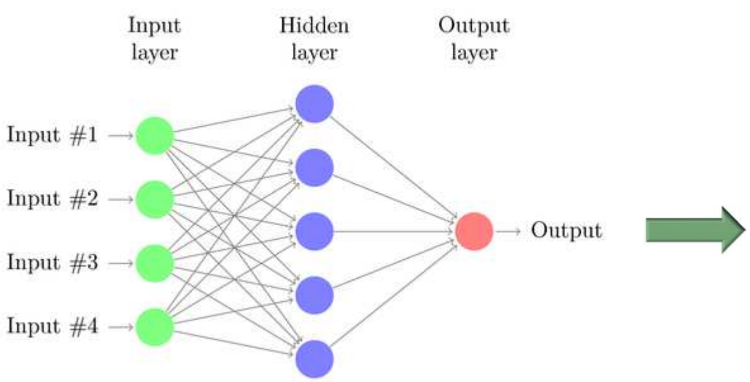


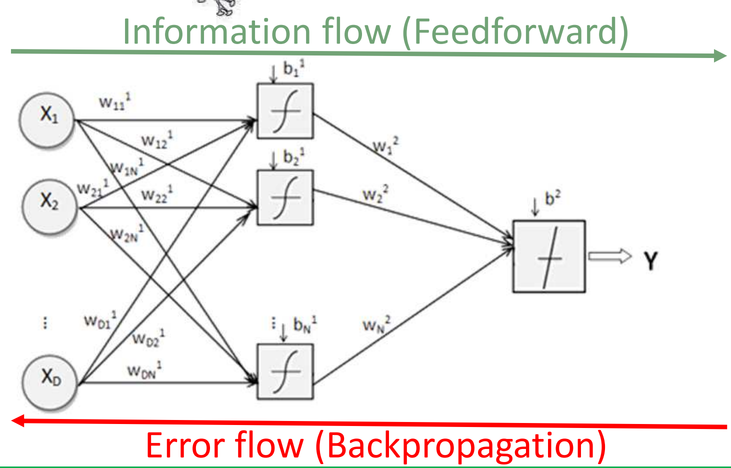
Drawback: Numerical Weather Predictions

Solution: Post-processing could be utilized to reduce the respective error.

Machine learning - ANN Brief







Theory: ANNs MLP can approximate any linear and nonlinear mapping.

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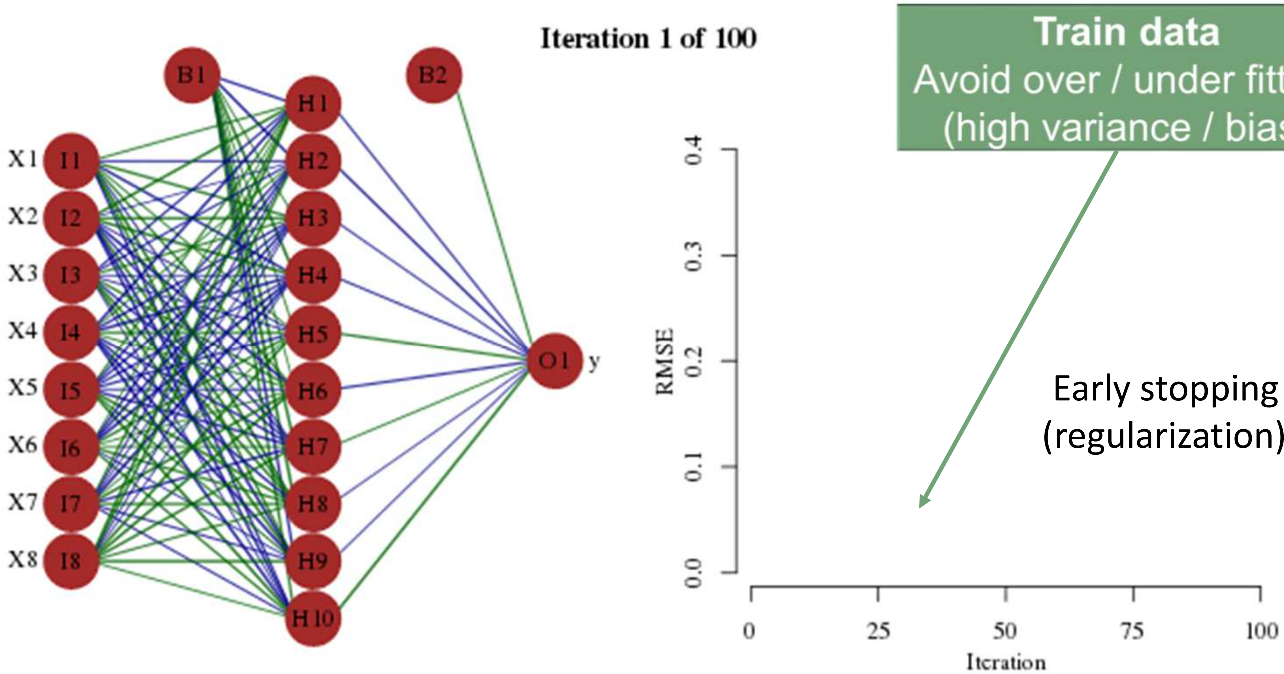
Machine learning - ANN Brief



Train data
Avoid over / under fitting
(high variance / bias)

Early stopping
(regularization)

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.

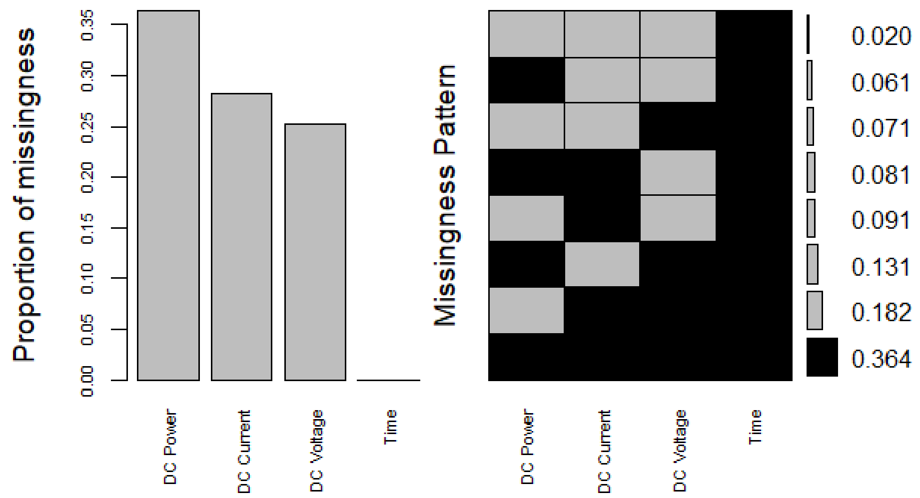
Solar Position Algorithm for
Solar Radiation Applications

NREL

Elevation Angle of the Sun (*AlS*)
Azimuth of the Sun (*AzS*)

Methodology – Data Quality Routine

- Identify missing (or erroneous) data, outliers and outages.
- Estimate system availability and sensor deviations.
- Correct data through data imputation techniques (kNN and Kalman filtering).



Day-ahead Forecasting

ANN Model Development

1. Data preparation

	Range (%)				
Training	30	40	50	60	70
Testing	30	30	30	30	30

Data set (1 year of hourly data)

Train Set (70 %) 255 Days	Test Set (30 %) 111 Days

G_{poa}	T_{amb}	RH	WS	W_{alpha}	AzS	AlS	P_{DC}

Measured: G_{poa}, T_{amb}, RH, WS, W_{alpha}

Calculated: AzS, AlS

2. ANN Design

- Architectural Design
- Validation
- Optimization

Training
(Train Set)

Validation
(Test Set (15 %))

Testing
(Test Set (15 %))

Methodology

Prediction Assessment Metrics - Validation

$$e_i = y_{i,forecasted} - y_{i,actual}$$

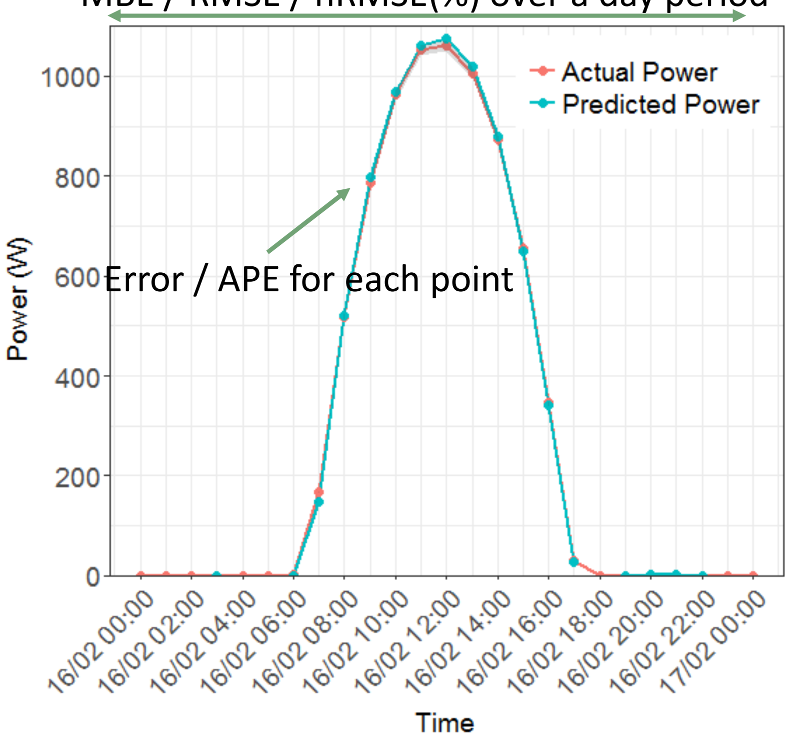
$$APE = 100 \times \left| \frac{y_{i,forecasted} - y_{i,actual}}{y_{i,actual}} \right|$$

$$MBE = \frac{1}{N} \sum_{i=1}^{N} e_i$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} {e_i}^2}$$

$$nRMSE(\%) = \frac{100}{P_{nominal}} \sqrt{\frac{1}{N} \sum_{i=1}^{N} {e_i}^2}$$

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



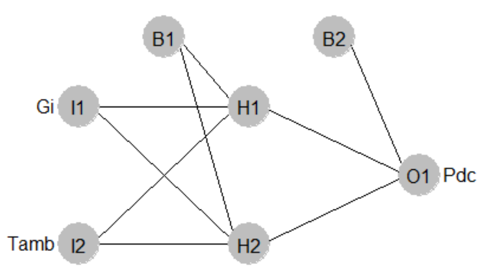
Model design: Input Parameters

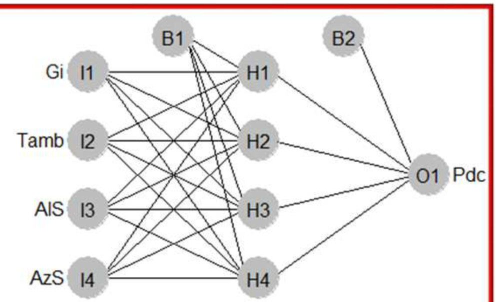
Continues

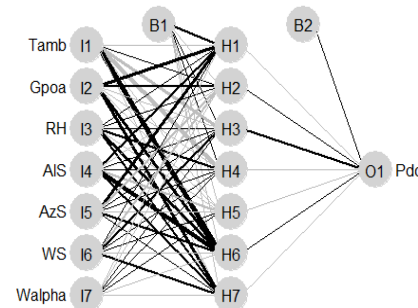
nRMSE(%) 6.60%

nRMSE(%) 6.30%

nRMSE(%) 7.90%







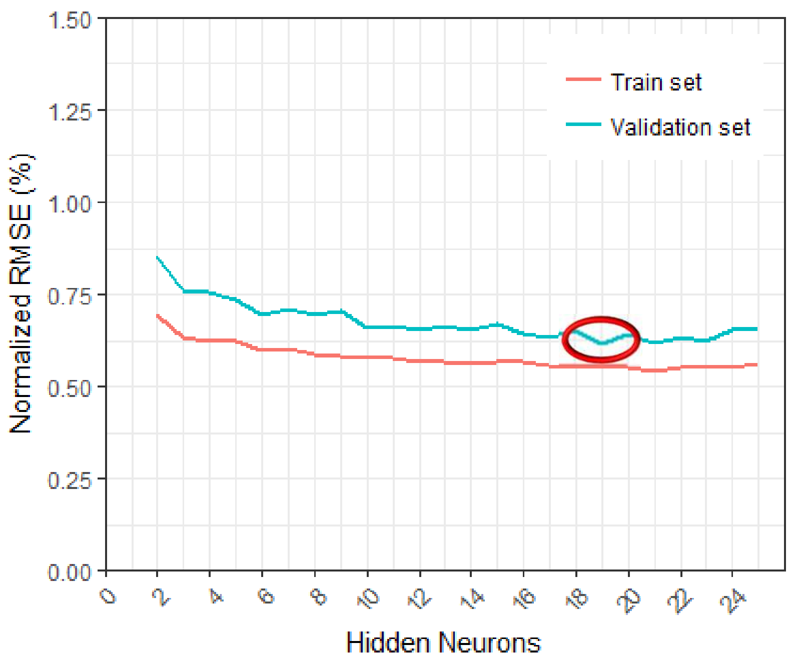
nRMSE(%) 6.50%

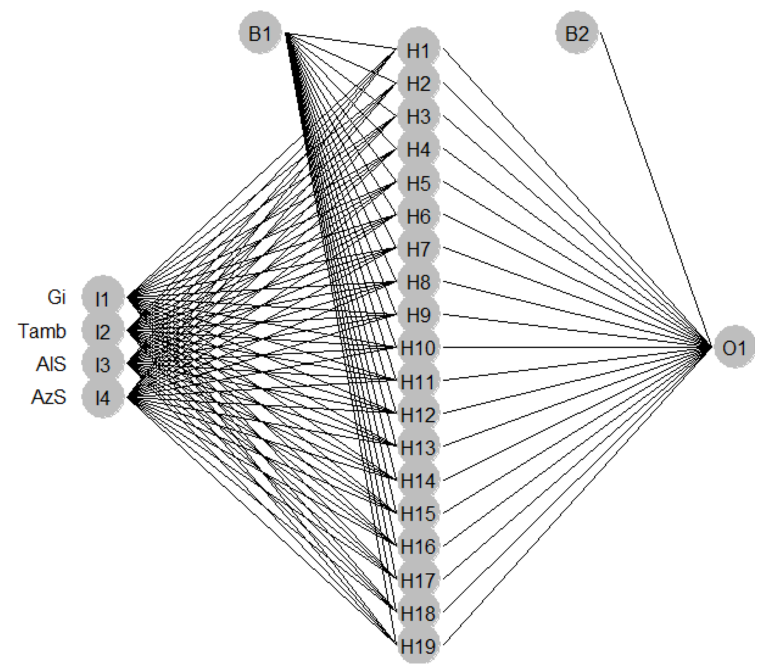
nRMSE(%) 6.15%

nRMSE(%) 7.77%

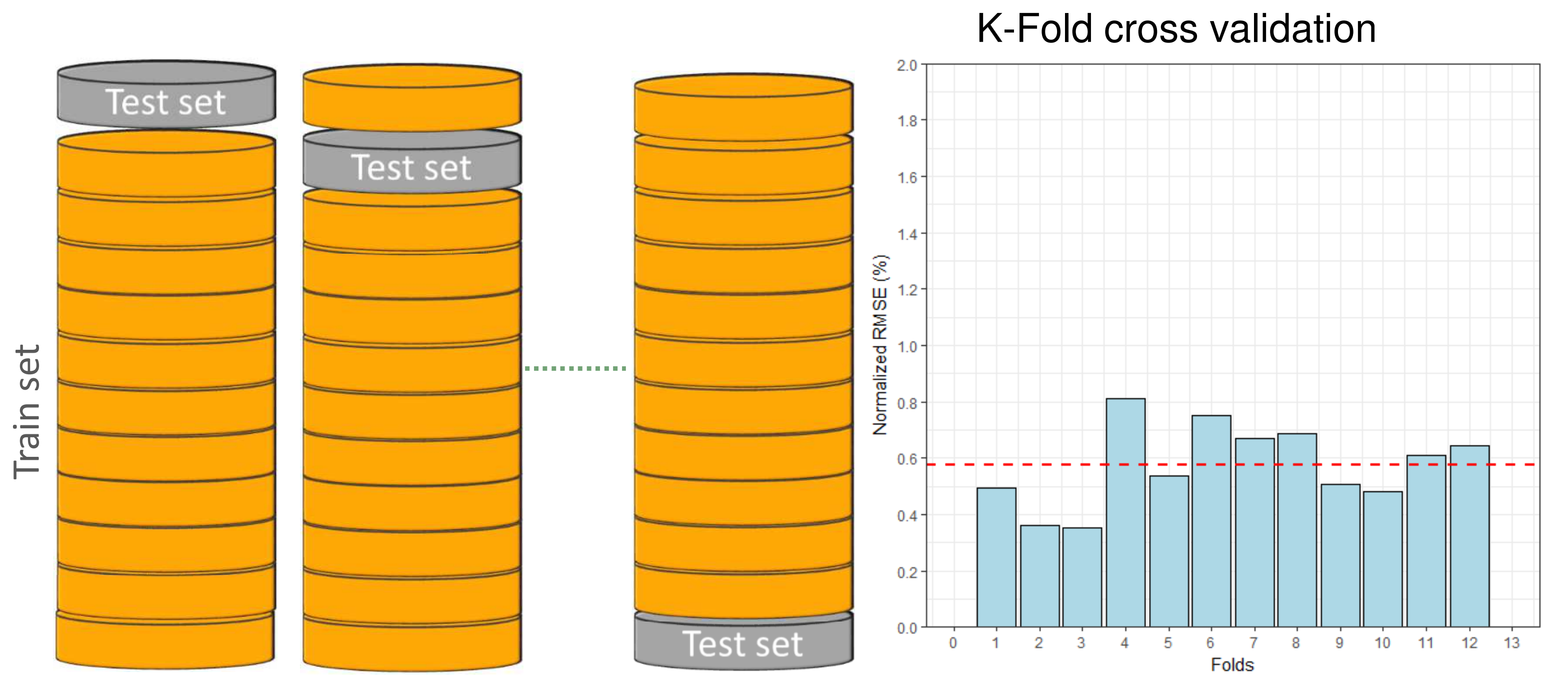
Random

Results – Model design: Number of Neurons



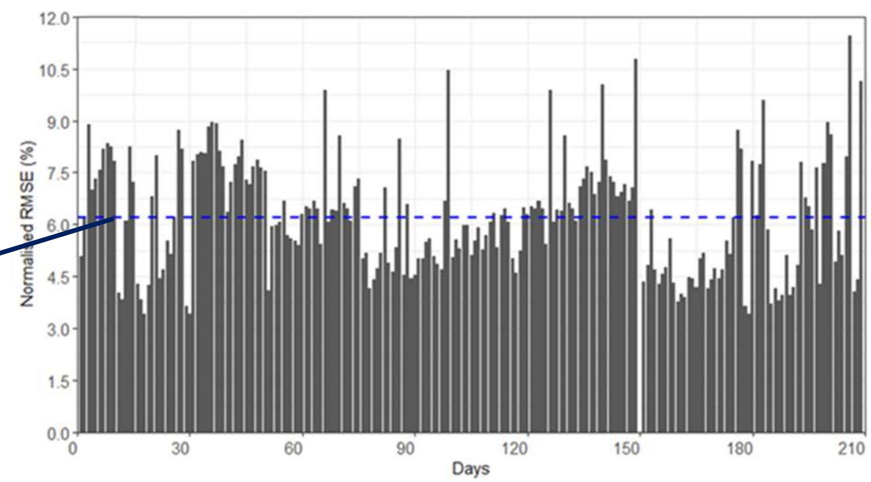


Model Performance - Cross validation



12-Folds nRMSE(%) ~0.5 ± 0.28 % (95 % confidence interval)

Model Performance



nRMSE(%) 6.10%

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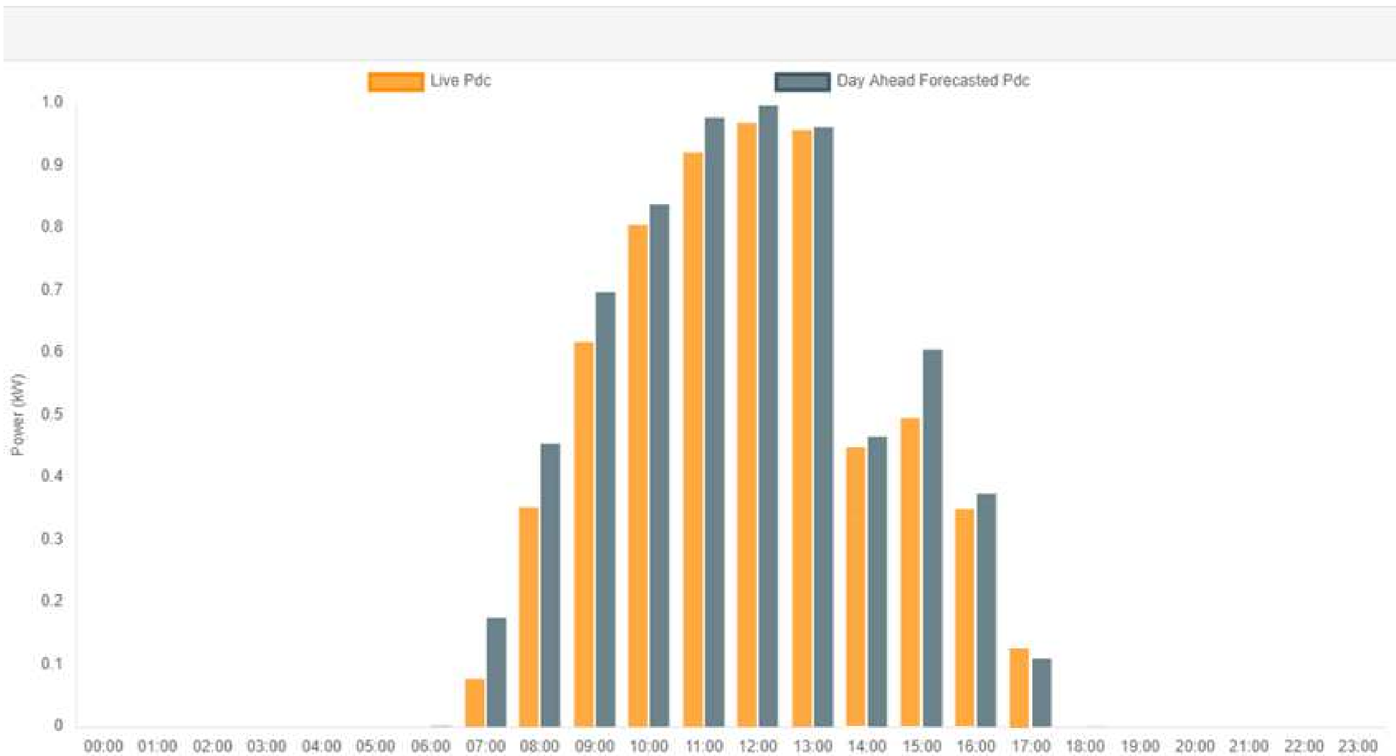
Model Performance



Intra-day Forecasting

Methodology

Data Quality Routines

↓

Data Pre-processing

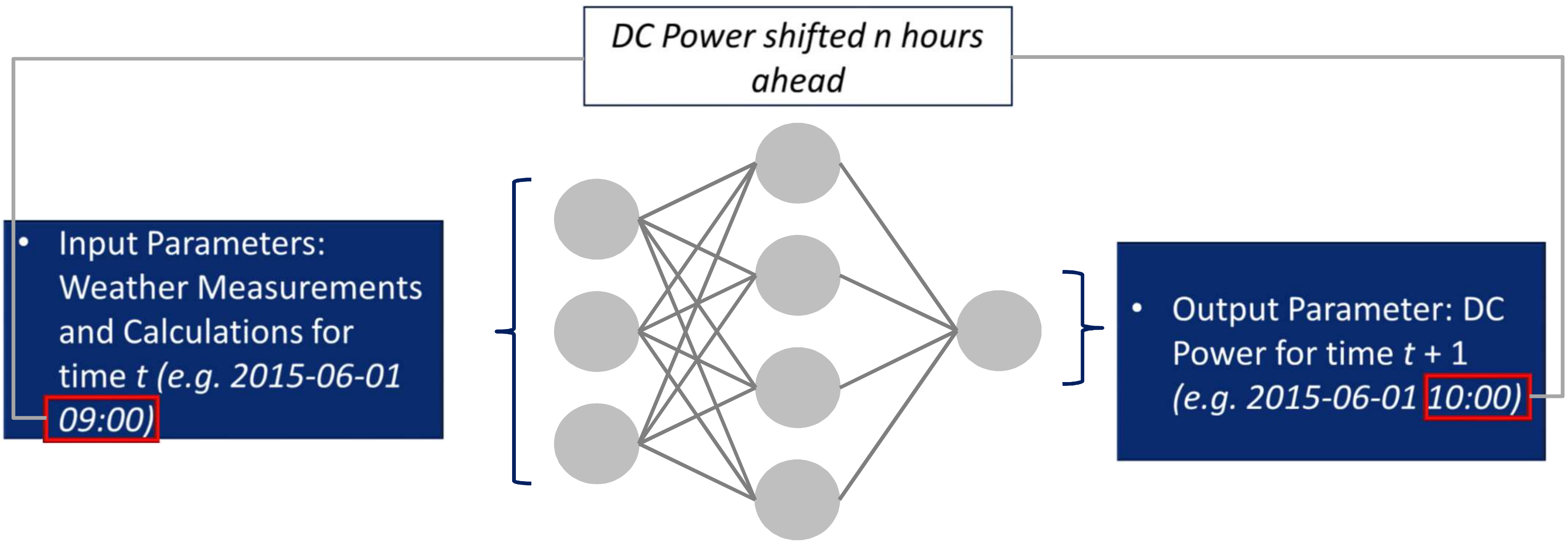
↓

ANN Model Development

↓

Assessment Metrics

Data Pre-processing (Training Set)



$$P_{DC}(t+n) = G_I(t) + T_{amp}(t) + \ldots$$

Methodology – ANN Model Development

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Training
(Train Set)

Validation
(Test Set (15 %))

Testing
(Test Set (15 %))

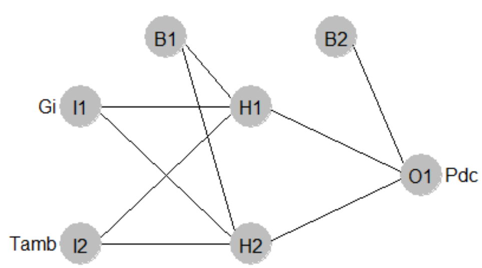
Results – Model design: Input Parameters

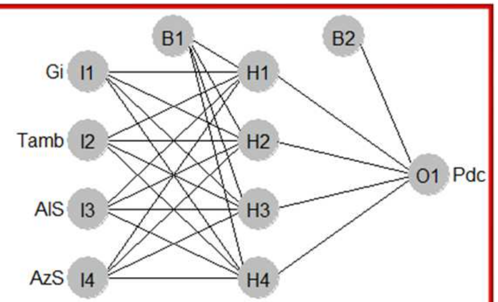
Continues

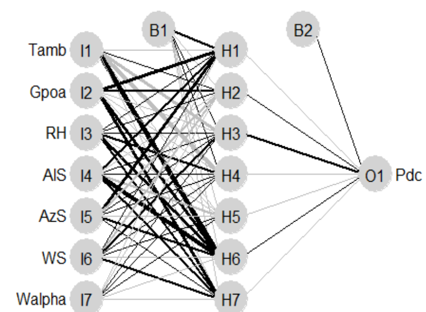
nRMSE(%) 5.60%

nRMSE(%) 4.70%

nRMSE(%) 5.90%







nRMSE(%) 5.50%

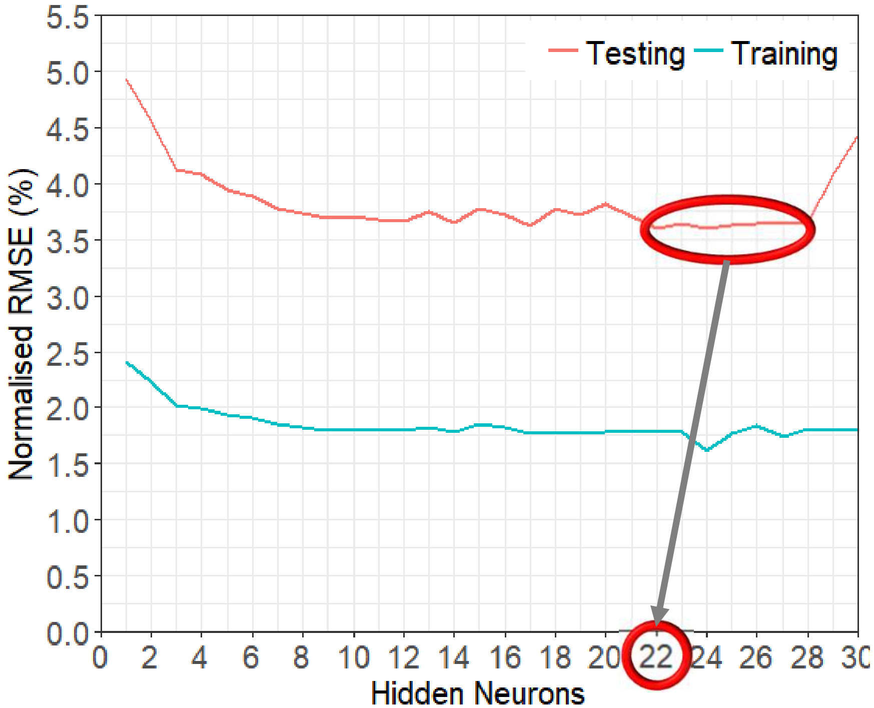
nRMSE(%) 4.60%

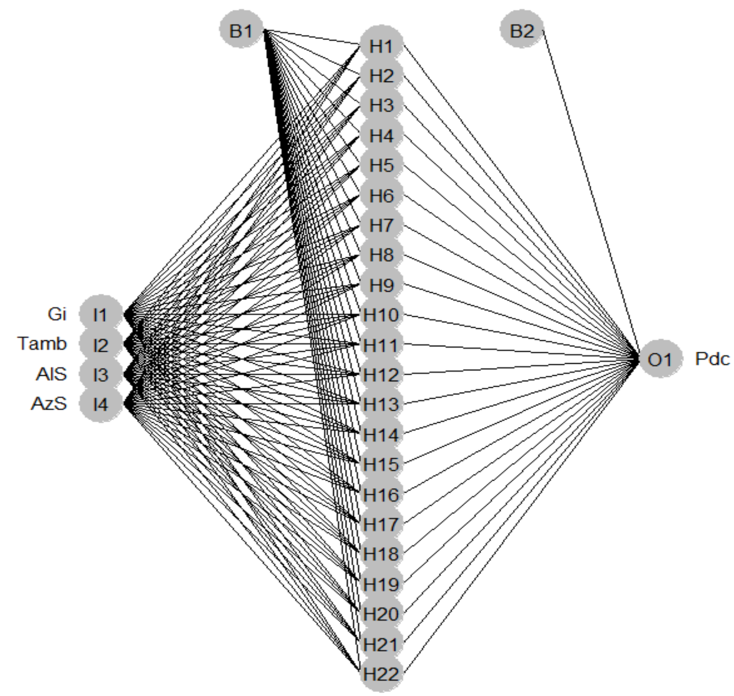
nRMSE(%) 5.77%

Random

$$P_{DC}(t+n) = G_I(t) + T_{amp}(t) + AIS(t) + AzS(t)$$

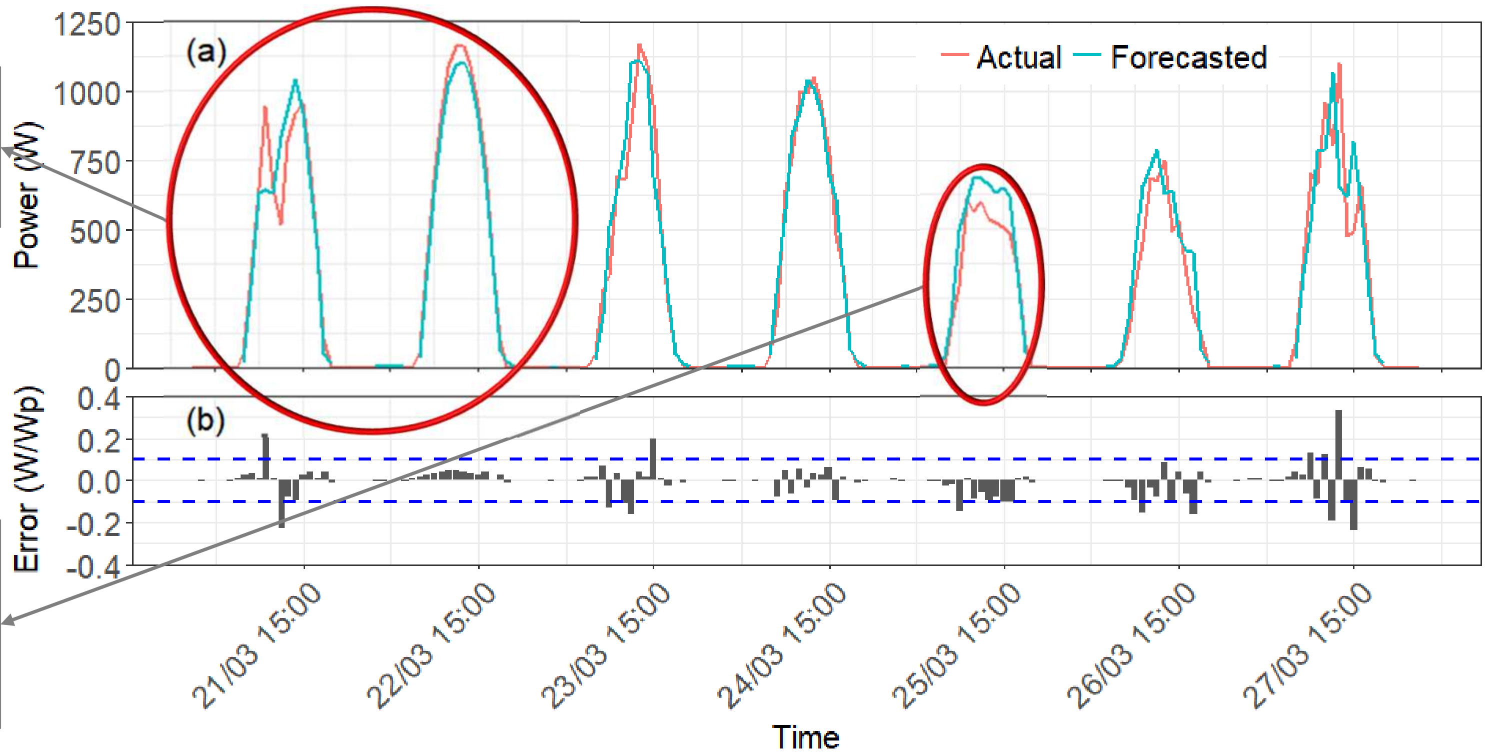
Results – Model design: Number of Neurons





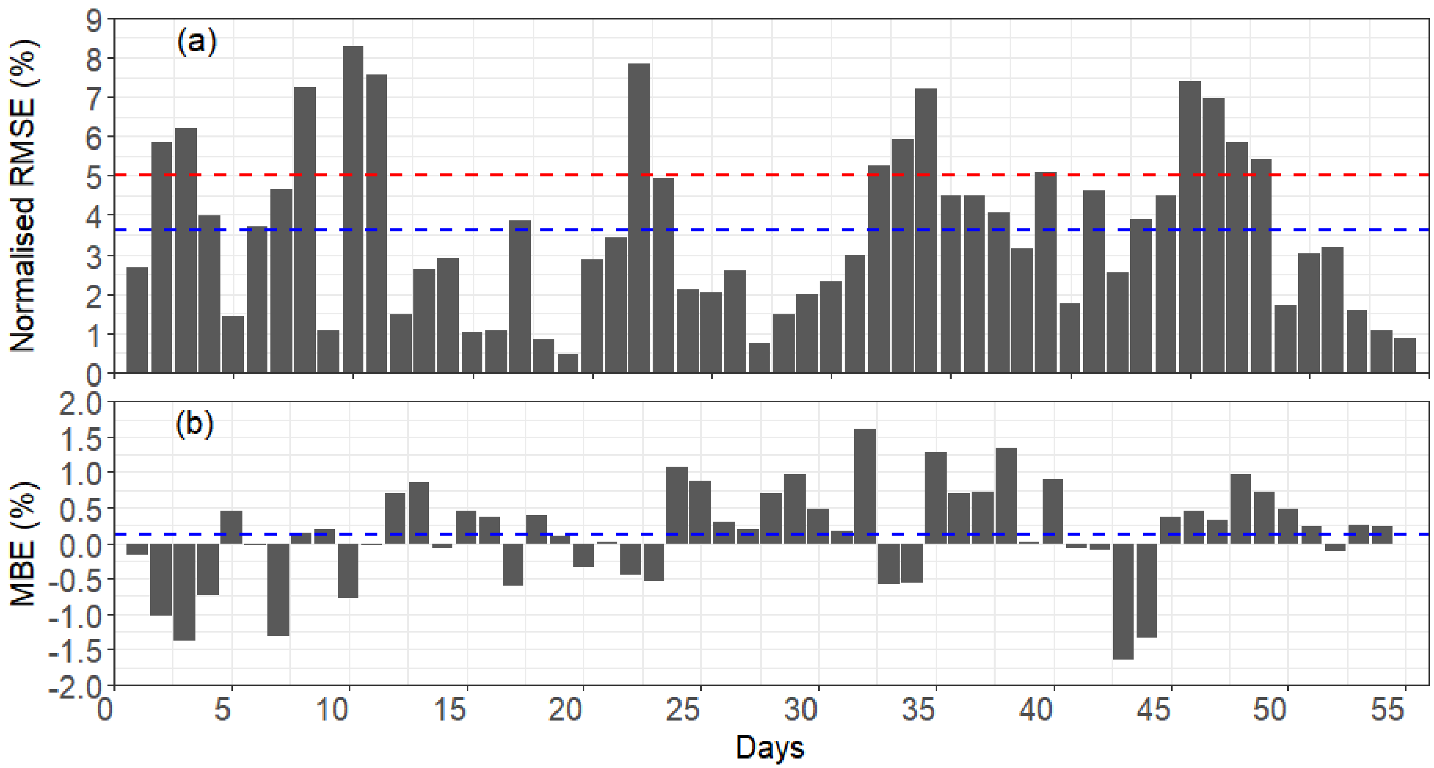
Results – Performance Assessment

- A typical week with clear sky and overcasted days.



- Post-processing will be performed to increase the accuracy.

Results – Testbed Period



Regional PV Power Forecasting

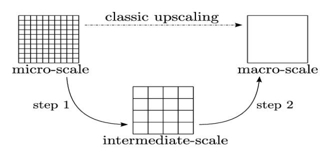
Methodology

Numerical Weather Predictions (Department of Meteorology)

CYPRUS DEPARTMENT OF METEOROLOGY

Forecasting Models for Point Forecasts

Upscaling
Point to Regional Forecasts



Regional Forecasts

Methodology

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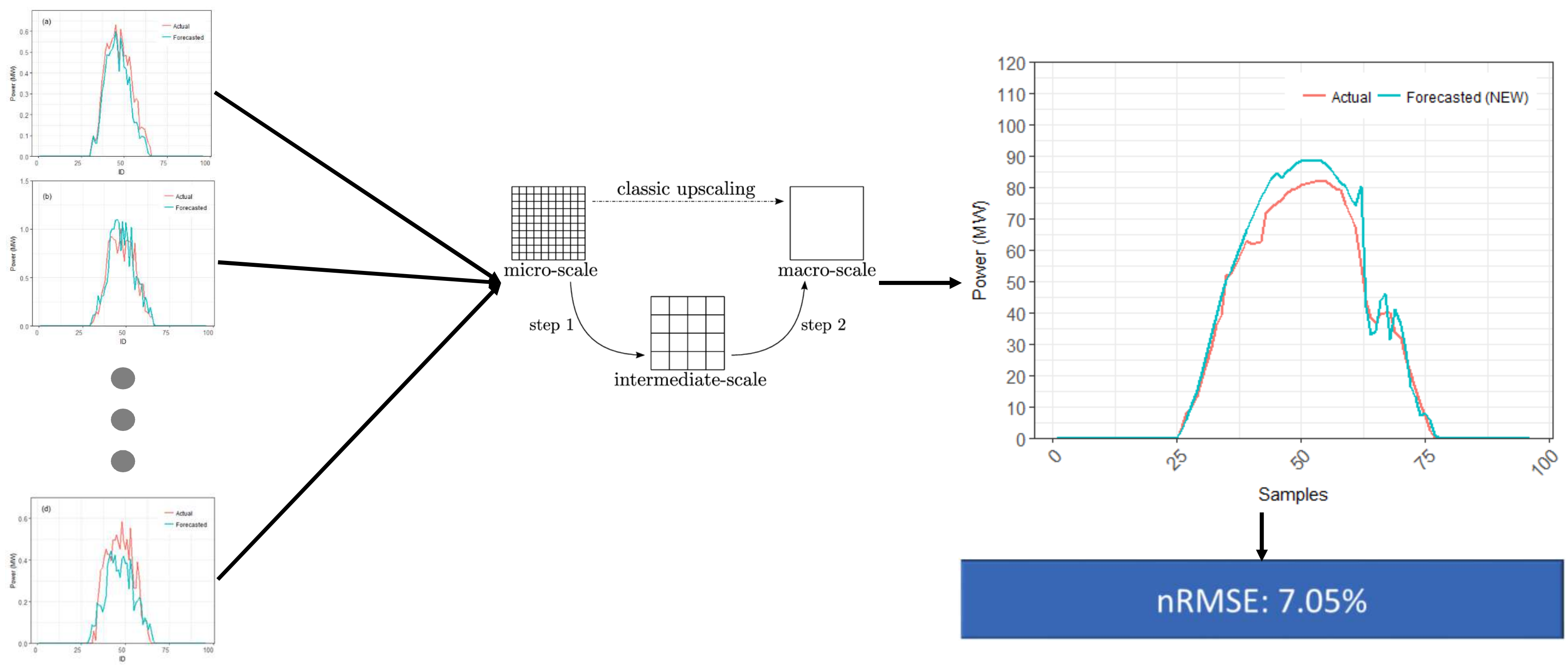
Results – Summary of PV Parks

PV Park	nRMSE	MBE
B1	8.74	2.10
B2	9.60	-1.19
B3	7.17	1.30
B4	6.10	0.95
B5A	8.39	1.32
B5B	6.44	1.13
B6	7.67	2.21
B11	7.47	1.76
B12	7.08	1.43
B13	9.10	2.62

nRMSE (%): 8.0% ±2%

PV Park	nRMSE	MBE
B15	8.20	1.47
MEMNON	8.55	-2.07
TSERI	7.50	1.21
APV	8.22	1.18
ATHIN.-POULLAS	8.06	0.89
WAVERON	7.55	1.27
NISOU	6.99	-0.75
PALIOMETOCHO	8.06	1.41
MALOUNTA	8.74	1.19
FRENAROS	9.29	-1.86

Results – Study Case (20/09/2018)



nRMSE: 7.05%

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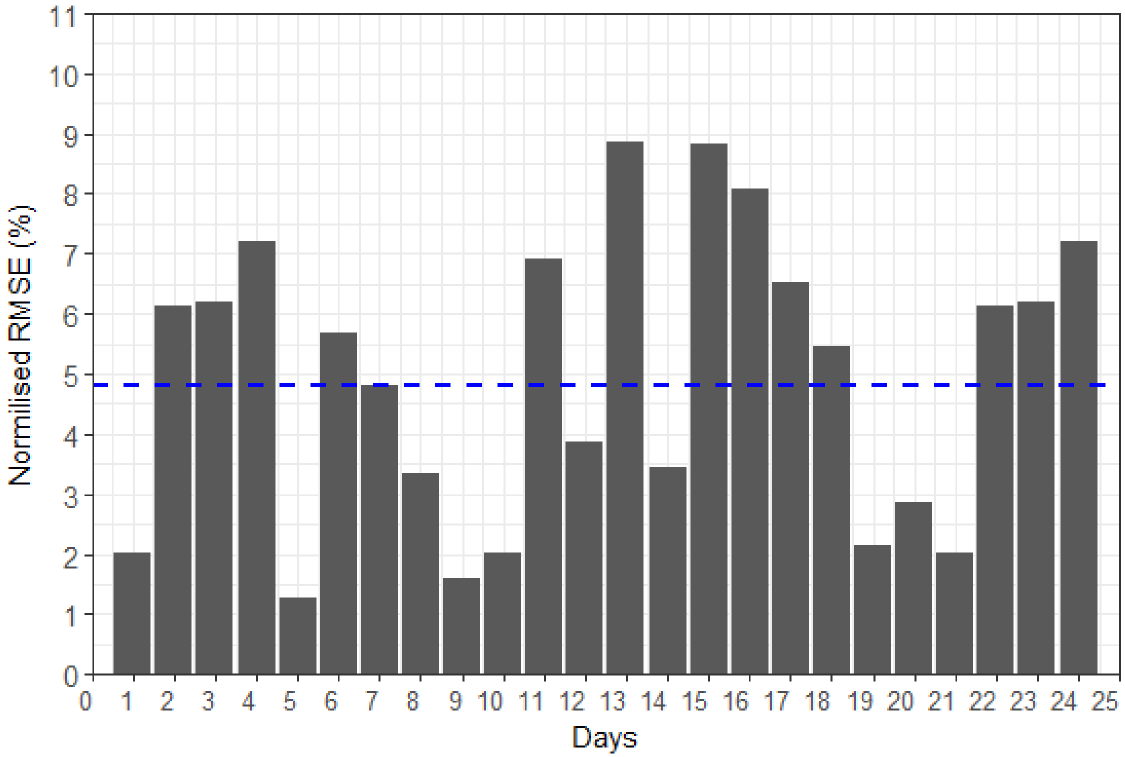
Results – Aggregated Forecasts for the whole of Cyprus

nRMSE: 4.80%



Conclusions

- Machine learning models could be utilized for the implementation of agile PV power forecasting techniques.
- NWP utilised for DA forecasting.
- NWP-free approach for intra-day forecasting
- The best-performing DA and HA forecasting model comprised by 4 inputs (G_I, T_{amb}, *AlS* and *AzS*) with randomly selected data from the 70% of the data set and 18 and 22 hidden neurons for the DA and intra-day forecasting respectively.
- The DA model demonstrated nRMSE of 6.10%
- The intra-day forecasting model demonstrated nRMSE of 3.63% and MBE 0.15% indicating no biases among the data over the testset period (55 days). For clear sky days the nRMSE was ≈ 1%.
- The regional DA PV power forecasting demonstrated an nRMSE of 8% ±2%.
- Post Processing techniques will be utilized to further increase the forecasting accuracy.

More Information…

Website
www.pvtechnology.ucy.ac.cy

Thank you for your attention

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