Optimum PV power forecasting modelling based on artificial neural networks

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Introduction

- A main challenge for ensuring large-scale deployment and sustainability of photovoltaic (PV) systems is to improve the accuracy of production forecasts, especially when a high concentration of such systems exists
- Accurate forecast of the day-ahead PV production is an important feature that can assist utilities and plant operators in the direction of energy management through optimal operation, dispatchability and operation mode planning
- This work presents the methodology to derive accurate day-ahead forecasts for PV systems, based on a machine learning artificial neural network (ANN) model which was optimised according to the input features and architectural parameters

Experimental Setup

- The outdoor test facility includes:
  - A fixed plane infrastructure for outdoor performance assessments at both the module and system level
  - The installed poly-c Si system was mounted in portrait arrangement on aluminum mountings, at the optimum annual energy yield plane-of-array (POA) angle for Cyprus of 27.5°
  - The PV system was connected to a data-acquisition platform, used for the monitoring and storage of meteorological and PV system outdoor operational data
  - The platform comprises of meteorological and PV operational measuring sensors connected to a central data acquisition system

Table I: Installed PV system technical characteristics.

System 1	
Modules	5 × poly-c Si 273 W_p
System power (datasheet)	1365 W_p
Installation date	01/06/2015
Efficiency	14.40 %

Figure 1: Grid-connected PV system used for the implementation of the optimal forecasting model.

Methodology

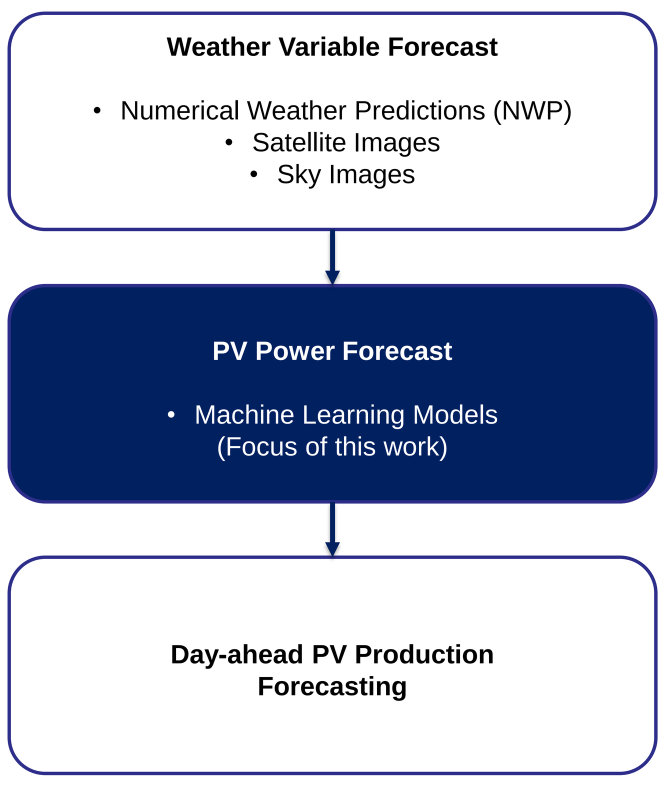

Figure 2: Forecasting methodology and focus of this study.

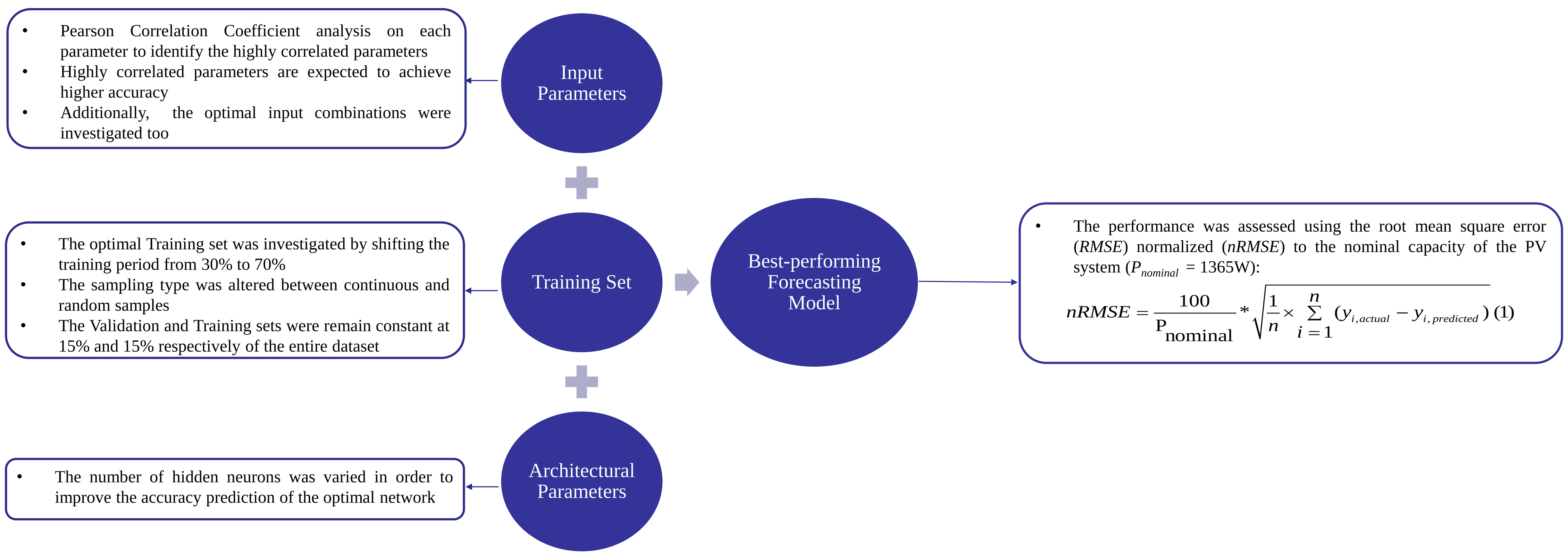

Figure 3: Methodology followed for the implementation of the optimal ANN forecasting model.

Results

Input Parameters

The optimal parameters comprised by G_I, T_{amb}, *AzS*, *AlS*, W_a, W_S, *RH*

Table II: Pearson Correlation Coefficient between PV power output and environmental factors

	Pearson Correlation Coefficient
	Maximum Power, P_{mp}
Incident global irradiance, G_I	0.9
Sun elevation angle, *AlS*	0.8
Relative humidity, *RH*	-0.7
Ambient temperature, T_{amb}	-0.5
Wind direction, W_a	-0.3
Wind speed, W_s	0.2
Sun azimuth angle, *AzS*	-0.01

Table III: Input feature parameters for ANN model training with the associated number of hidden layer neurons and the corresponding *nRMSE*.

Input features	Hidden Layer Neurons	*nRMSE* (%)
G_I, T_{amb}	2	1.15
G_I, T_{amb}, *AlS*	3	1.10
G_I, T_{amb}, *RH*	3	1.18
G_I, T_{amb}, *RH*, *AlS*	4	1.10
G_I, T_{amb}, W_{alpha}, W_S	4	1.19
G_I, T_{amb}, W_S, *AlS*	4	1.10
G_I, T_{amb}, W_S, *RH*	4	1.12
G_I, T_{amb}, *AzS*, *AlS*, W_a, W_S, *RH*	7	0.87

Training Set

The optimal training set comprised by the 70% of the actual data set

Table IV: Test set validation and the corresponding *nRMSE* for different training periods and sampling types.

Dataset length	Continuous data *nRMSE* (%)	Random data *nRMSE* (%)
30%	1.30	0.99
40%	1.28	0.97
50%	0.98	0.91
60%	0.95	0.85
70%	0.90	0.80

Architectural Parameters

The optimal architectural parameters consist of 1 hidden layer and 12 hidden neurons.

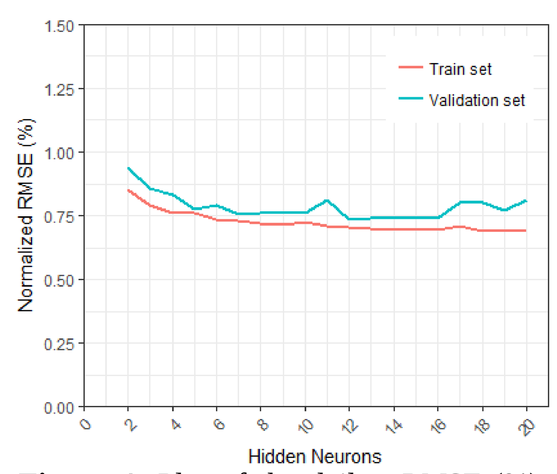

Figure 4: Plot of the daily *nRMSE* (%) for training and testing set for a single hidden layer.

Best-performing Forecasting Model

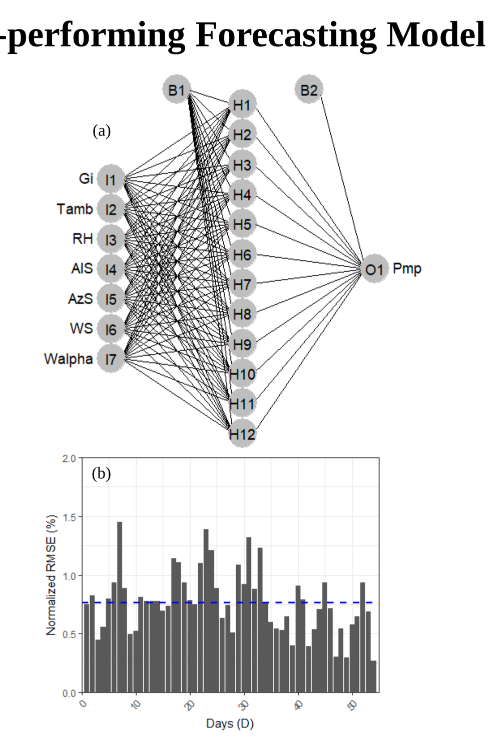

Figure 5: (a) Network interface diagram and (b) The daily *nRMSE* of the model was on average 0.76%.

Conclusions

- PV production forecasting based on machine learning algorithms such as ANNs can successfully be utilized to implement more agile forecasting procedures.
- For the development of an optimal ANN model a procedure with subsequent stages of training and testing steps was followed, whereby the devised ANNs were assessed by tuning their input features and network architecture.
- The final model consists of 7 input parameters (G_I, T_{amb}, *AzS*, *AlS*, W_a, W_S, *RH*), 1 hidden layer, 12 hidden neurons and 70% of the actual data set was the training set. The optimal model demonstrated an average daily *nRMSE* of 0.76% while the majority of days were below 0.50%.

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