Integrated regional solar PV forecasting method by hybrid method: Case Study of an Indian State

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Development of Indigenous Solar Forecasting System

- This work was carried out under the umbrella of Indo German Energy Programme, Green Energy Corridors project of GIZ GmbH. This was under overarching activity of " Development of indigenous forecasting system at National Institute of Wind Energy".
- A consortium of Overspeed GmbH, University of Oldenburg, Suntrace GmbH and SGS environmental systems was selected on the basis of an international tender.

Research Question

- To develop a day –ahead forecasting system for control area (an Indian State) using combination of physical and statistical approach.

- To identify few reference solar PV power plants and perform the forecast for the identified power plants. Arriving at the forecast for the entire state based on the forecasts of the selected reference power plants.

Highlights of the work

- Regional Forecasting for an Indian State using upscaling approach. First time this research is attempted in India.

- Used as much as Indian datasets as possible (Data from Solar Radiation Resource Assessment station, National Centre for Medium Range Weather forecasting (NWP) data, Solar power plant data (static and dynamic).

- Step by step Scientific approach followed. Used combination of physical and statistical models.

Data Sets Used

- NWP Data [1,2,3]

NWP Model Name	Spatial Resolution	Original Temporal resolution	Interpolated Temporal resolution (not given by the provider)
ECMWF	0.25 degree x 0.25 degree (Approx. 25 km * 25 km)	3 hours	15 minutes
NCMRWF	0.25 degree x 0.25 degree (Approx. 25 km * 25 km)	1 hour	15 minutes
GFS	0.25 degree x 0.25 degree (Approx. 25 km * 25 km)	1. ho ur	15 minutes

- Solar Radiation Resource Assessment (SRRA) Data [4]
  - Data from one of the stations under this network was used for the modelling exercise.
  - SRRA network is a series of high quality, well maintained radiation measurement stations maintained all over India.

Data Sets Used (contd…)

- State of the art, secondary standard pyranometers are installed for the measurements of the radiation.
- All the parameters are run through state of the art quality control algorithms.

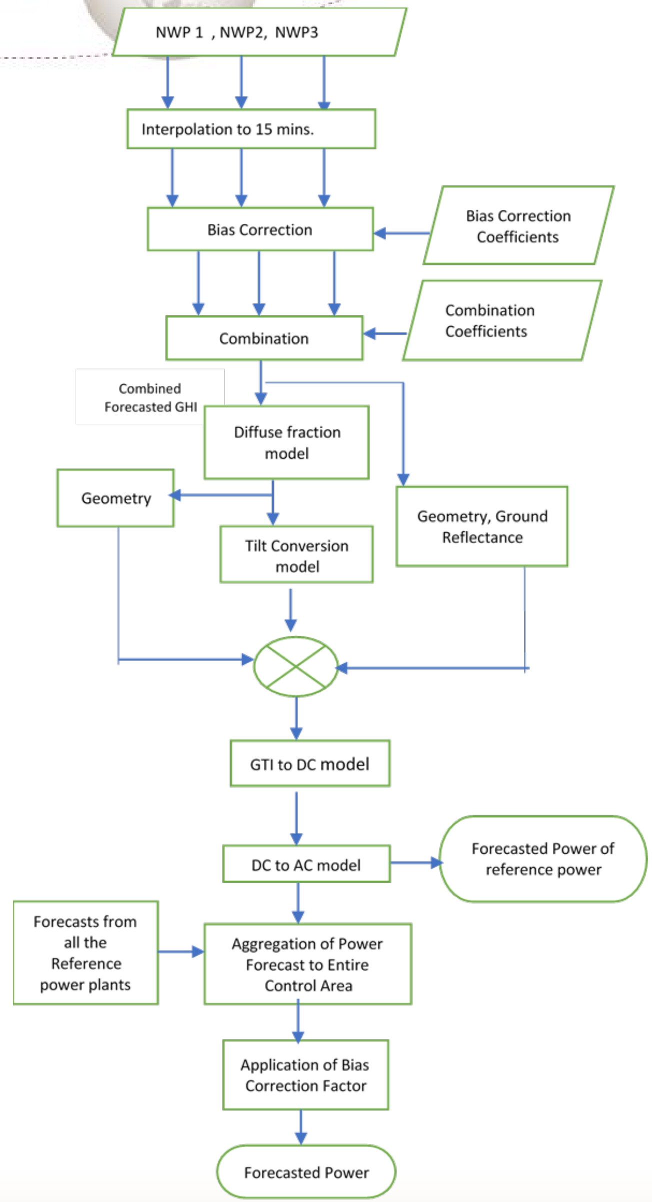
Power Plant Data

- Static and dynamic data (AC Power data) were received from totally 12 reference power plants were utilized for the forecasting model development.

Data Sets Used (contd…)

Parameters from Individual Power Plant	**Availability of Data from the Power Plant**
Static Data	√
GHI	×
GTI	×
Ambient Temperature	×
Module Temperature	×
DC Power	×
AC Power (Individual, Aggregate)	√

Methodology



Important Steps in Model Chain

- Bias correction is performed by Standard fourth order polynomial function of clear-sky index and Cosine of Zenith angle.
- Combination of NWP's was done as per linear regression. The coefficient of the equation was found out by fitting with ground measured data. SRRA data from one of the ground measurement stations was used for fitting.

$$Combi_{NWP} = a1 * NWP1 + a2 * NWP2 + a3 * NWP3 + a4$$

Important Steps in Model Chain(Contd…)

- Chandrasekar and Kumar- Diffuse Fraction Model was included in the model chain [6].
- Diffuse sky model by Klucher was employed [7].
- GTI to DC model is using the formula according to power plant information and PV module specifications.

$$DCPower = GTI * Number\ of\ Panels * Panel\ Area * Efficiency * (1 + \mathrm{alpha} * (\mathrm{temp\_mod} - 25))$$

alpha= temperature coefficient of PV module.

Important Steps in Model Chain (contd…)

- Schmidt and Sauer model was used for DC to AC conversion [8]. The following equations define the model.
- The parameters are found by fitting the DC power and AC power data of the power plant where the measurements were available.

$$Ploss = Pself + Vloss.Pout + rloss.P^2out$$

when rloss is positive:

$$\eta * = -\frac{1+v*_{loss}}{2.r_{loss}.p_{in}} + \sqrt{\frac{(1+v*_{loss})^2}{(2.r*_{loss}.p_{in})^2} + \left(\frac{p_{in}-p*_{self}}{r*_{loss}.p_{in}^2}\right)}$$

when rloss is negative:

$$\eta * = -\frac{1+v*_{loss}}{2.r_{loss}.p_{in}} - \sqrt{\frac{(1+v*_{loss})^2}{(2.r*_{loss}.p_{in})^2} + \left(\frac{p_{in}-p*_{self}}{r*_{loss}.p_{in}^2}\right)}$$

Important Steps in Model Chain (contd…)

- Twelve reference power plants were selected for the upscaling process.
- Important criteria that were considered while choosing reference power plants [9]:
  - Regional Spread of the power plants was ensured.
  - Representation for core areas of installed capacity.
  - Representation of technology/ size mix..
  - Representation of power plants in different climatic zones as per installation was considered.

Important Steps in Model Chain (contd…)

- Upscaling was attempted by two methods, Proportional Sum and Nearest neighbor method.

- Proportional Sum Method:

$$Upscaled\ solar\ power\ forecast\ (MW) = \frac{\sum Solar\ \ power forecast\ of\ reference\ plants\ (MW)}{\sum Installed\ Solar\ capacity\ of\ reference\ plants\ (MW)} * \sum Installed\ Solar\ capacity\ of\ entire\ State\ (MW)$$

Important Steps in Model Chain (contd…)

Nearest Neighbour Method

- All the power plants are mapped according to the most proximate neighboring reference farm.

$$Forecast\ of\ non-reference\ power\ plant\ (MW) = \frac{Solar\ power\ forecast\ of\ neighbouring\ farm\ (MW)}{Installed\ capacity\ of\ neigbouring\ reference\ plant\ (MW)} * Installed\ capacity\ of\ non\ reference\ \ plant(MW)$$

$$Upscaled\ solar\ power\ forecast\ (MW) = \sum Forecast\ of\ all\ non\ reference\ farms\ (MW) + \sum Forecast\ of\ all\ reference\ farms(MW)$$

Results

Bias Correction Results:

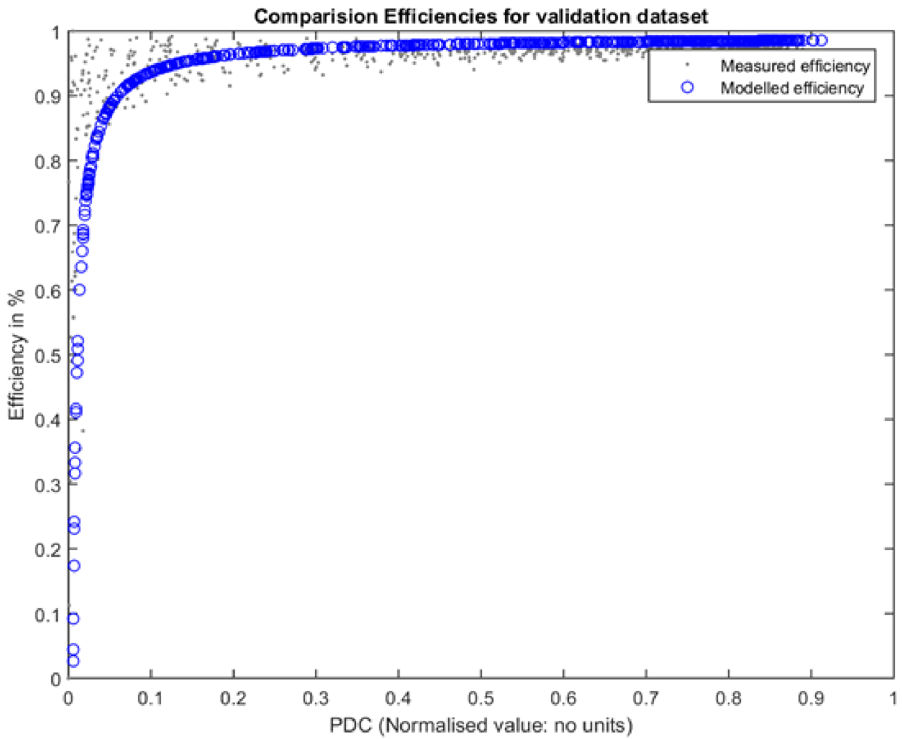
- Data from 1st May 2017 - 31st January 2018, was used for finding the coefficients of polynomial function.
- SRRA data from one of the stations was used for fitting the equation.
- Table showing the KPI values for the process

NWP name	Raw/ Bias Corrected	NRMSE(%)	NBias (%)
NWP1	Raw	X1	Y1
	Bias Corrected	0.93X1	0.133Y1
NWP2	Raw	1.37X1	2.238Y1
	Bias Corrected	1.11X1	0.3813Y1
NWP3	Raw	1.504X1	2.094Y1
	Bias Corrected	1.236X1	0.287Y1
Combination	Bias Corrected (ECMWF, NCMRWF and GFS)	0.888X1	-0.0056Y1

Results

DC to AC Model

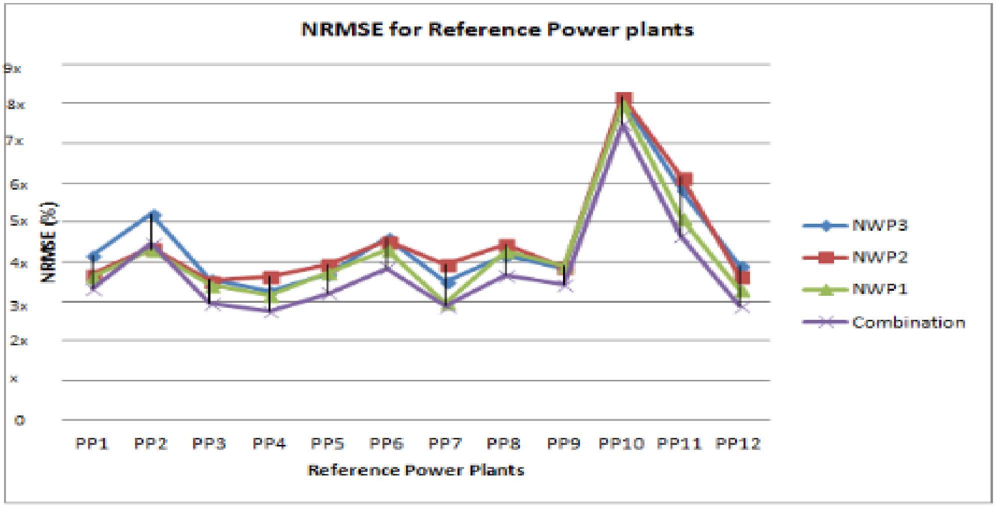
- The inverter coefficients were derived from 10 MW power plant were DC power and AC power data were available.



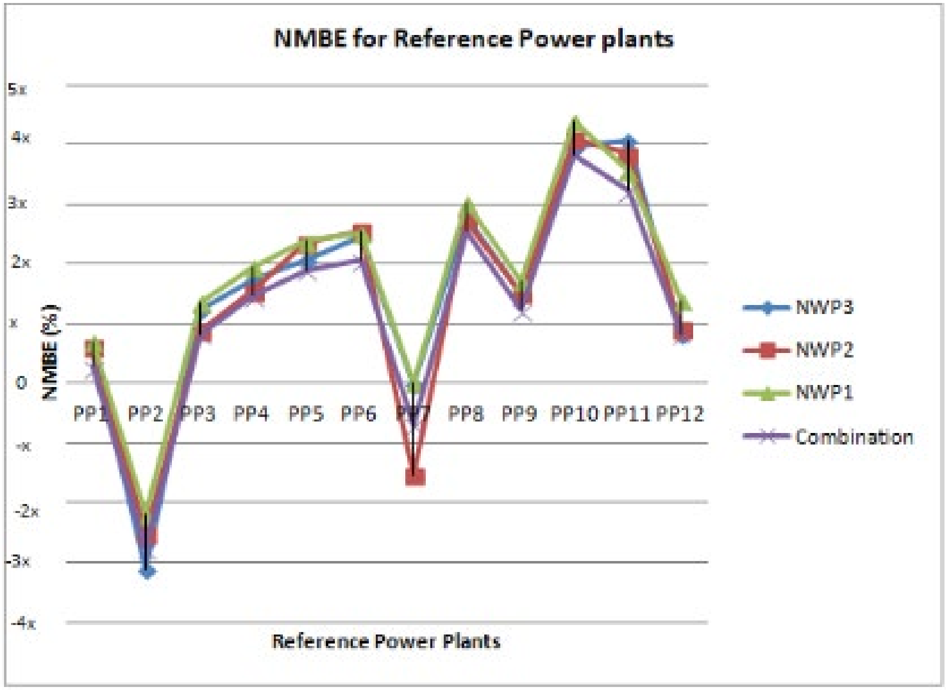
Results

Performance of forecast for Reference Power Plants

- The time period of validation of forecasts is 8th December 2018 to 26th February 2019.



Results (contd…)



Results (contd…)

Performance of Aggregate forecast based on historical data sets

- NWP1 forecasts are the best performing compared to other NWP's, the upscaling of forecasts for the entire state is attempted with NWP1 model chain.
- Two types of upscaling techniques (proportional sum and nearest neighbor) are evaluated.
- Forecast accuracy evaluation at the AC Power end is performed for a period from ***8th December 2018 to 26th February 2019***, which is the same period considered for individual power plants.

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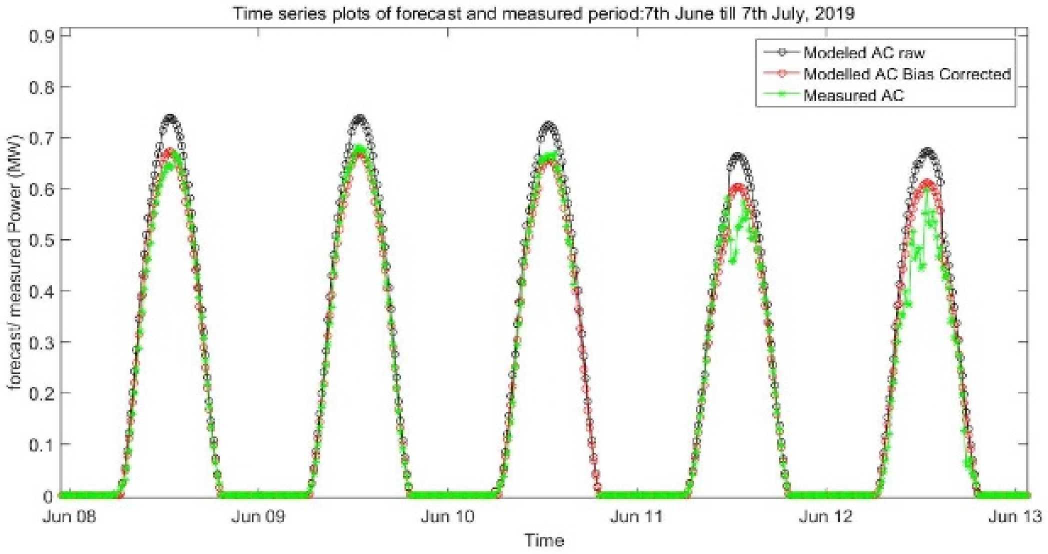
Results (contd…)

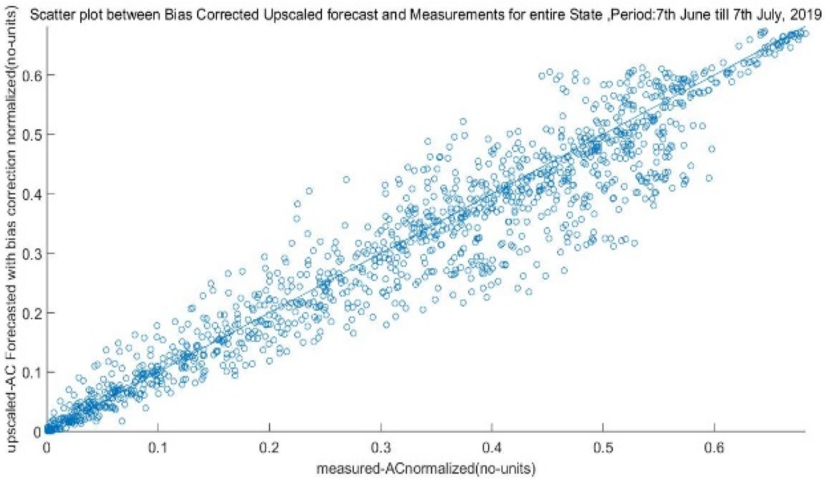
DATE RANGE	Proportional Sum		Nearest Neighbor	
	NRMSE (%)	NMBE (%)	NRMSE (%)	NMBE (%)
08-12-2018 to 10-12-2018	X1	Y1	1.92X1	2,358Y1
11-12-2018 to 04-01-2019	0.989X1	0.989Y1	1.89X1	2.33Y1
05-01-2019 to 21-01-2019	0.966X1	0.966Y1	1.85X1	2.28Y1
22-01-2019 to 21-02-2019	0.944X1	0.944Y1	1.81X1	2.23Y1
22-02-2019 to 26-02-2019	0.912X1	0.912Y1	1.75X1	2.15Y1

Results of Operational Forecast System

- Operational forecasting system for solar power generation was setup based on NWP1 forecasts.
- Operational forecasting system is implemented with “Proportional Sum” Method as it was showing better results.
- Forecast accuracy evaluation at the aggregate AC Power is for the period between 7th June 2019 to 7th July 2019.



Results (contd…)



DATE RANGE	Bias Correction Factor at AC power	NRMSE (%)	NMBE (%)	NMAE (%)
7th June till 7th July, 2019	No	X1	Y1	Z1
7th June till 7th July, 2019	Yes	0.922X1	-0.786Y1	0.847Z1

Discussion and Conclusion

- Grid operators primarily require the forecast for the entire control area that will help them in scheduling and grid management.
- In this work, development of indigenous day ahead forecasting for an Indian state was attempted.
- Combination of physical and statistical methodologies was adopted.
- REMC's being established in India will support the state SLDC's in this very crucial functionality of aggregate forecasting [10].
- The forecasting system developed is showing reasonably good accuracy.
- It was seen that combination of NWP models is improving the forecasting accuracy of individual plants.

Discussion and Conclusion

- Some of the steps taken to finetune the forecasting system that are being undertaken are as follows:
    - Combination methods (linear and non-linear).
    - Advanced diffuse fraction models.
    - Algorithms for including uncertainty information in the forecasts which will be very important for the grid operators to manage and plan for reserves.
- Only measured AC power data from the power plant being received. Receiving other meteorological parameters will help to generate location specific coefficients for the models.
- Receiving the AC power data from other non-reference power plants will assist to fine-tune the forecasts based on historic generation data.

Discussion and Conclusion

- Important to receive the data in least possible time resolution:
  - In the analysis of historic aggregate forecast and measurements, there were time-shift between the two signals.
  - Historic measurement data was received in 15 minutes time resolution.
  - The time shift was eliminated in operational forecasting system when the data was started to receive in one minute time resolution.

ONGOING AND FURTHER WORK

- Satellite-based forecasting for intra-day time horizon.
- Improvement modelling the influence of aerosols.
- Improvement of soiling modelling [11].

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Thank You for the patient hearing!

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Back Up Slides

- Klucher Model Equations

$$I_T = \frac{(I_H - I_D) * \cos(\psi)}{\sin(\alpha)} + I_D\left(\frac{1+\cos\varepsilon}{2}\right)\left(1 + Fsin^3\left(\frac{\varepsilon}{2}\right)\right)\left(1 + Fcos^2(\psi)sin^3(90-\alpha)\right)$$

(9)

$$F = 1 - \left(\frac{I_D}{I_H}\right)^2$$

(10)

I_T =insolation on surface tilted toward the equator at angle ε

I_H=total insolation received on horizontal surface

I_D=diffuse insolation received on horizontal surface

(α) = solar elevation angle

(ψ)= angle between sun direction and normal direction of tilted surface

Back Up Slides (Contd…)

Diffuse Fraction model by Chandrasekar and Kumar:

$$k_d = 1.0086 - 0.178k \; for \; k \leq 0.24$$

$$k_d = 0.9686 + 0.1325k + 1.4183k^2 - 10.1860k^3 + 8.3733k^4 \; for \; 0.24 < k \leq 0.8$$

$$k_d = 0.197 \; for \; k > 0.8$$

Where k_d= diffuse fraction, k= clearness index